THE AUSTRALIAN NATIONAL UNIVERSITY

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CRAWFORD SCHOOL of Economics and Government
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TECHNICAL EFFICIENCY AND ITS DETERMINANTS IN GANSU, WEST CHINA

Sizhong Sun

PACIFIC ECONOMIC PAPERS
No. 355, 2006

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2006

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Papers submitted for publication in this series are subject to double-blind external review by two referees.

The Australia–Japan Research Centre is part of the Crawford School of Economics and Government, The Australian National University, Canberra.

ISSN 0 728 8409
ISBN 0 86413 308 1

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Technical Efficiency and Its Determinants in Gansu, West China[1]

Sizhong Sun[2]

This paper analyses the technical efficiency problem in Gansu Province, West China, using firm-level cross-sectional data. Compared with previous studies, which mostly focus on industries, this paper focuses on a geographic area instead. By applying the stochastic frontier framework, this paper arrives at four major findings: first, resource-based firms are more technically efficient on average than non-resource-based firms; second, foreign investment is beneficial to the improvement of technical efficiency; third, there is no evidence that ownership affects the technical efficiency of firms in Gansu province; and fourth, bigger firms tend to operate with more technical efficiency than smaller firms.

Introduction

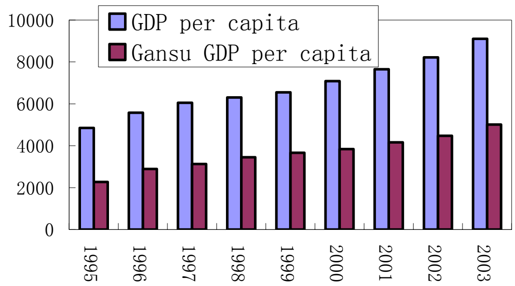
As is well known, China's economy is progressing at a rapid speed. From 1990 to 2003, the average annual GDP growth rate (calculated with GDP in constant 1985 prices) was 8.2 percent, and per capita income also increased greatly, with per capita annual disposable income of urban households in 2003 over five times that of 1978 (in constant 1978 prices). However, some problems have arisen in the process of rapid economic development, such as income inequality and regional disparities. Since 1978, the east and south regions of China (located in the coastal area) have grown comparatively more quickly than the western region, reflecting both the impact of government policy and the advantage of physical location (Démurger et al., 2002; Golley, 2003). For example, the first five special economic zones, namely Shenzhen, Zhuhai, Shantou, Xiamen, and Hainan, are all located in the costal area which is obviously more convenient in interacting with the world geographically. In 2003, western China accounted for 72 percent of China's total area; the population accounted for 29 percent of China's total; while its GDP only accounted for 17 percent of China's total GDP. This regional disparity has already attracted government attention. How to develop the west of China, a less developed region, has become a major focus of the Chinese Government policy. This paper will employ a stochastic production model and technical inefficiency model to analyse the technical efficiency of firms located in Gansu province in West China, and try to find the determinants that affect firms' technical efficiency.

Basically, this paper has four aims: First, to measure the technical efficiency of firms in Gansu Province, China, in order to observe firms' technical performance, that is, how far away these firms are from their Production Possibility Frontier (PPF). Second, this paper endeavors to identify industry-specific factors that affect firms' technical efficiency. By incorporating different factors and a series of dummy variables in the technical inefficiency model, the significance of these factors will be tested. Third, it endeavors to establish whether resource-based firms are more technically efficient than other types of firms. Gansu province is heavily dependent on natural resources, and many resource-based firms are agglomerated there. Thus we would like to find out whether they are operating more efficiently, which presumably results from the benefit of the agglomeration of resource-based firms and from comparative advantage. Fourth, it endeavours to derive the policy implications for economic development, based on the empirical results.

This paper focuses on Gansu province because it has two distinct underlying characteristics in economic development and factor endowment: it is relatively under-developed, and meanwhile it is rich in natural resources. For GDP per capita, Figure 1 gives a comparison between Gansu and the national level. Since 1995, the GDP per capita of Gansu has been well below that of the national level. In 2003, GDP per capita in Gansu was 5,012 RMB, while the national average level was 9,101 RMB, that is, Gansu's GDP per capita was only about 55 percent of the national level. On average, from 1995 to 2003 GDP per capita of Gansu was only 54 percent of the national level. Figure 2 compares Gansu's GDP growth rate with the national average. We can see that Gansu's GDP growth rate is no higher than the national average in most of years since 1995, which means that the gap in GDP per capita is not going to narrow down unless the population growth rate is sufficiently lower than the national average, which is unlikely to happen.

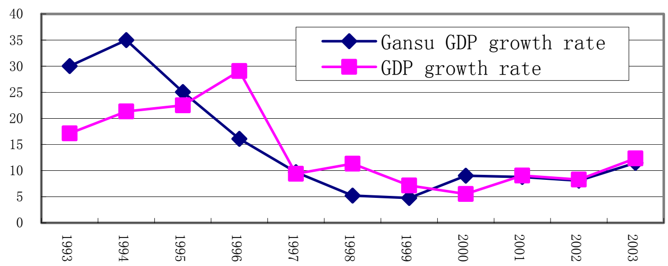
Gansu is well known for its reserve of natural resources. Gansu has 11 minerals that rank as China's largest reserves, 32 minerals that rank in China's top five, and 51 minerals that rank in China's top 10. The reserve of nickel-cobalt ranks in the world's top three, the reserve of zinc ranks in China's top three, and the reserves of copper ranks in China's top four. In addition, owing to its natural endowment, Gansu's industry is also heavily resource-based. The added value of the non-ferrous metals and the metallurgy industries accounts for 25 percent of the total added value of industry. In 2003, the output of electrolytic aluminium was 500,000 tonnes, which accounted for 9.3 percent of the national output. During the period January–May 2005, the added value of the eight main industries (all resource-based) accounted for 80 percent of total provincial output.

Figure 1 Comparison of GDP per capita (unit: RMB)



Source: National Bureau of Statistics of China, various issues

Figure 2 Comparison of GDP growth rate (unit: %)



Source: National Bureau of Statistics of China, various issues

Literature review

The stochastic production frontier is a tool used for analyzing the technical efficiency of firms and its determinants. Briefly speaking, it derives the unknown production possibility frontier of firms from the data sample, and compares the firms' actual output with the prediction of the derived PPF to calculate the firms' technical efficiency. Furthermore, the distribution of technical efficiency (either the mean, the variance, or both) is assumed to be a function of perceived determinants to test what impact they have on technical efficiency.

Jefferson (1990) examines the influence of firm supervision on firm efficiency in China. By using a sample of 120 iron and steel enterprises, he found the measured efficiency of enterprises under local government supervision was higher than that of the enterprises supervised by the central government. Kalirajan and Cao (1993) look at the effect of economic reform on enterprise performance. They examined not only technical efficiency, but also allocative efficiency and scale efficiency, and found that in 1988 the Chinese iron and steel industry achieved about 60 percent of its potential output on average. Wu (1995) applies a time-varying production frontier model (a panel study) to examine the productive efficiency in the Chinese iron and steel industry, with data covering 61 state and local firms. He found that Chinese firms on average achieved 69-82 percent of their potential output during 1984-92; that firm age is positively related to enterprise efficiency; that firm ownership and economies of scale do not have a significant effect on the efficiency performance of firms; and that firms' location has a positive effect on performance owing to the gain from economies of agglomeration. Movshuk (2003) uses panel data to evaluate the impact of major reform initiatives on enterprise performance in China's iron and steel industry. His major findings are: in the mid-1990s, technical efficiency did not improve significantly, or even deteriorated, despite the upward shift in the production possibility frontier; and the largest steel enterprises did not have a pronounced efficiency advantage over smaller ones, that is, firm size seemed to have no significant effect on technical efficiency.

Chinese agriculture is also a popular field to which the stochastic production model is often applied. Different factors that may affect farm efficiency have already been examined, among which are agricultural education, agricultural institutions, and credit sources. Regarding education, the empirical results generally support the idea that education will improve agricultural production efficiency. For example, Wang, Cramer and Wailes (1996) find that Chinese farmers with higher education are more efficient. Cheng (1998) finds that the effect of the level of the household head's schooling on grain output is significantly positive. Liu and Zhuang (2000) also find that education is positively correlated with efficiency, and that there is a pressing need to improve intangible human qualities in rural China. As an example of institutional impact, Wan and Cheng (2001), and Fleisher and Liu (1992) examine the effect of land fragmentation. They find that a new land tenure institution that emphasises consolidation will significantly improve the production efficiency of China's agriculture. Lohmar, Zhang, and Somwaru (2002) find that land rental activity increases aggregate agricultural production by transferring land from low-intensity farm households to high-intensity farm households. Meanwhile, Liu and Zhuang (2000) demonstrate that credit encourages technological, chemical, and biological innovations (that is, it has a positive effect on efficiency) by acting as an insurance mechanism in agrarian economies. Their study also shows that a farmer's nutrient intake has a positive effect on farm productivity.

In other fields, Tong (1999) uses the stochastic production frontier to analyse production efficiency and spatial disparities across China's township and village enterprises (TVEs). He uses a panel data in his study, and finds that the production efficiencies of TVEs on average improved between 1988 and 1993, but that spatial disparities exist, namely the production efficiency of TVEs located in the coastal region was higher than those located in the non-coastal region. The mean production efficiencies he estimated ranged from 59 percent to 82 percent.

In general, these studies have focused on a particular industry, while this paper will deal with the technical efficiency of firms located in a particular area —Gansu province. Doing this means an implicit assumption must be made, that is that the production function of firms can be described by such generalised inputs as physical capital stock and labour, and that firms share the same production possibility frontier. This in turn requires that all industry-specific and firm-specific inputs can be transformed into these two generalised factor inputs. That is to say, for example, for an agricultural firm, land is one input, however we can not include land directly into our estimation. Land must be transformed into physical capital stock instead. Obviously, to bundle all firms together, this is the tradeoff that must be made. However, doing this also enables us to test the hypothesis concerning variables that do not vary within the same industry. For example, in this paper we can test whether resource-based firms operate more technically efficiently than non-resource-based firms, while this cannot be done if we just look at the resource-based industries. This kind of issue cannot be tested if we just measure the technical efficiency of resource-based firms in the resource-based industry.

Theoretical methodology

Technical efficiency and its measurement

According to Farrell (1957), total economic efficiency can be decomposed into two components: technical efficiency and allocative efficiency. Technical efficiency reflects the firm's ability to maximize the output for a given set of inputs (operate at the boundary of a production possibility frontier), or the firm's ability to minimize inputs used for a given set of output; and allocative efficiency reflects the firm's ability to use inputs in optimal proportions given their market prices and the production technology they used.

The measurement of technical inefficiency can be classified into two categories: input-oriented measures and output-oriented measures. Koopmans (1951) gave them formal definitions. This paper will use an output-oriented measure. Its formal definition is as follows:

An output vector $y \in L(y)$ is technically efficient, if

and only if, $y^{'} \notin L(y)$ for $y^{'} \geq y$

This definition says that given inputs and technology, any output that is higher than the current output is not available to the firm if the firm is already technically efficient.

Many different methods have been adopted to estimate technical efficiency. Two major approaches are data envelopment analysis (DEA) and the stochastic production frontier model. The former involves mathematical programming, and the latter uses econometric methods. This paper will use the latter approach.

Stochastic production frontier model

The stochastic frontier model is a widely used approach in measuring technical efficiency. It was first proposed independently by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). These models capture both the technical inefficiency and other random shocks that affect output and are outside the control of producers, based on the idea that the influences of these two factors can at least be separated. The model can be summarised as:

$$\ln(y_i) = x_i\beta + v_i - u_i \qquad \text{i=1, 2, … , N} \tag{1}$$

where y is the output; x is the vector of inputs; β is a vector of production parameters; the random error v (two-sided “noise” component) accounts for the effect of all random factors, such as the measurement error, the effects of weather, and luck. The v s are assumed to be independently and identically distributed (iid) as normal random variables with mean zero and constant variance σ_v^2, and are also assumed to be independent of u_s and the inputs vector x. The u_s s are non-negative random components and capture technical inefficiency, since the non-negative assumption of u ensures that the firm’s actual production point always lies beneath the stochastic frontier and the gap thus measures technical inefficiency. Hence the error term is actually composed of two components. The OLS estimate of the equation will have a consistent estimate of $(\beta_1,...,\beta_k)$ if the u_s s are uncorrelated with the input vector, but not the intercept β_0 (unless the mean of u_s is zero). So in order to obtain the estimate of the production technology parameters vector, β, and to estimate the technical efficiency of each firm, the distribution of u must be assumed. Commonly, u_s are assumed to be independently distributed as a non-negative truncation (at zero) of the normal distribution $N(m_i, \sigma_u^2)$.

Each firm's technical efficiency can be measured as the ratio of actual output against potential output, as follows:

$$TE_i = \frac{E(Y_i | u_i, x_i)}{E(Y_i | u_i = 0, x_i)} = e^{-u_i}$$

Furthermore, in order to obtain the specific factors that affect each firm's technical efficiency, following Battese and Coelli3 (1995), the mean of u (i.e. the technical inefficiency term) can be specified as:

$$m_i = z_i \delta + w_i \tag{2}$$

where z_i is a p×1 vector of firm-specific variables that may influence the technical efficiency of the firm, and δ is the vector of parameters to be estimated.

Then, conditioned on the exogenous factors x and z, the mean log technical efficiency and log output of firm i are $E[\ln y_i | x_i, z_i] = x_i \beta - z_i \delta - w_i$ and $E[\ln TE_i | x_i, z_i] = -z_i \delta - w_i$ respectively. Hence the partial effect of the factor z_{ik} (the k th factor of vector z_i) is:

$$\frac{\partial E[\ln y_i | x_i, z_i]}{\partial z_{ik}} = \begin{cases} -\delta_k, z_{ik} \notin x_i \\ \beta_l - \delta_k, z_{ik} \in x_i \end{cases}$$

$$\frac{\partial E[\ln TE_i | x_i, z_i]}{\partial z_{ik}} = -\delta_k$$

These are the semi-elasticity of output and technical efficiency of firm i to the exogenous factors, that is the percentage change of output/technical efficiency for one unit change of the exogenous factor.

Equation (1) is the stochastic production frontier model and equation (2) is the technical inefficiency model. They are linked to each other by the one-sided error term u. Battese and Corra (1977) parameterise the variance terms of u and v as $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$, where σ^2 is the variance of output conditioned on inputs. This says that the production uncertainty comes from two sources: pure random factors and technical inefficiency. Hence if γ, the proportion of uncertainty coming from technical inefficiency, is equal to zero, then it means actually there is no technical inefficiency. This can be used to test whether technical inefficiency is present in the firm. To estimate equations (1) and (2), a three-step procedure is employed4. An OLS estimation is carried out to obtain the estimation of β and σ as the first step; then as the second step, the estimation of β and σ is adjusted accordingly to correct for the bias; as the third step, the Davidon-Fletcher-Powell iterative maximisation routine is carried out to obtain the ML estimates.

Econometric specification

To apply the framework of Battese and Coelli (1995), the production function form needs to be specified. In practice, both the translog form and the Cobb-Douglas form are usually adopted. The translog form is more flexible in permitting substitution effects among inputs, and is claimed to be a relatively dependable approximation to reality (Giulkey, Lovell, and Sickles, 1983), while the Cobb-Douglas form is simple and commonly used. The likelihood ratio test for the production function form, that is translog vs. Cobb-Douglas, is made to see which fits the data sample better (see Table 3). The production function is specified as follows:

Model 1: Translog: $\ln y_i = \beta_0 + \beta_1 \ln k_i + \beta_2 \ln l_i + \beta_3 \ln k_i \ln l_i + v_i - u_i$

(CD: $\ln y_i = \beta_0 + \beta_1 \ln k_i + \beta_2 \ln l_i + v_i - u_i$)

Model 2: Translog: $\ln y_i = \beta_0 + \beta_1 \ln k_i + \beta_2 \ln l_i + \beta_3 \ln k_i \ln l_i + \beta_4 wrb_i + v_i - u_i$

(CD: $\ln y_i = \beta_0 + \beta_1 \ln k_i + \beta_2 \ln l_i + \beta_4 wrb_i + v_i - u_i$)

where y is the output, k is the physical capital, l is the labor, and in Model 2, the dummy variable wrb is added to capture the fact that the production function of resource-based firms may be different to those of non-resource-based firms.

For the technical inefficiency model, 11 variables are used (see Table 1), as follows:

Model 1:
$$m_i = \delta_0 + \delta_1 ete + \delta_2 rde + \delta_3 lie + \delta_4 yoo + \delta_5 yoo2 + \delta_6 ite + \delta_7 wrb + \delta_8 wfi + \delta_9 wp + \delta_{10} db + \delta_{11} dm$$

Model 2:
$$m_i = \delta_0 + \delta_1 ete + \delta_2 lie + \delta_3 yoo + \delta_4 yoo2 + \delta_5 wrb + \delta_6 wfi + \delta_7 wp + \delta_8 db + \delta_9 dm$$

where in Model 2, two variables, the R&D expense (rde) and the expense in introducing technology (ite), are left out because of data constraints (most of firms reported zero expenditure on these two variables).

Thus, in general, four models are estimated. They are Model 1-1 (the production frontier model 1 plus technical inefficiency model 1), Model 2-1 (the production frontier model 2 plus technical inefficiency model 1), Model 1-2 (the production frontier model 1 plus technical inefficiency model 2), and Model 2-2 (the production frontier model 2 plus technical inefficiency model 2).

In the technical inefficiency model, the aim is to predict firms' technical efficiency, and to see whether resource-based firms are more technically efficient than non-resource-based firms, whether foreign investment help firms to improve their technical efficiency, whether ownership and firm size have an effect on technical efficiency, after controlling for a series of factors, such as the firm's training expenses, their R&D expenses, the expense of introducing new technology, the expense of the labor insurance, and the age of the firm. For the first three factors, a negative effect on inefficiency is expected, since training is likely to make employees more skillful, and R&D will help to improve the firm's technology level, while introducing technology will obviously improve the technology level of the firm, and thus improve technical efficiency. Expenditure on labor insurance is expected to have a positive effect on a firm's technical inefficiency since the insurance should have a negative influence on the employees' incentive to work hard. The age of the firm is considered to have a quadratic effect on firms' technical efficiency since when firms are young, they may be too inexperienced to operate efficiently, and when firms are too old, inertia may make them unresponsive to adjustments to achieve the technical efficiency.

Table 1. Variables and their descriptions

Variable Name	Description
y (lny)	The output of the firm, proxied by the sales income of the firm. (the log form of the output)
k (lnk)	The capital input of the firm, proxied by fixed capital asset. (the log form of the capital)
l (lnl)	The labour input of the firm, proxied by the number of average annual workers. (the log form of the labour force.)
ete	The employee's training expenses by the firm (its log form).
rde	The firms' R&D expenses (its log form).
lie	The firms' expenses on labour insurance (its log form).
yoo	Years of operation of the firm.
yoo2	The square of years of operation of the firm.
ite	The firms' expenses on introducing the technology (its log form).
wrb	The dummy variable, indicating whether the firm is resource-based. If the firm is resource-based, wrb=1.
wfi	The dummy variable, indicating whether there is foreign investment in the firm. If there is foreign investment in the firm, wfi=1.
wp	The dummy variable, indicating the business type, that is whether the firm is privately owned. If the firm is privately owned, wp=1. Otherwise, wp=0.
db	The dummy variable, indicating the firms' size. If the firm is big in size, db=1. Otherwise, db=0.
dm	The dummy variable, indicating the firms' size. If the firm is medium-sized, dm=1. Otherwise, dm=0.

4 The data

Data description and variables construction

The data set is cross-sectional, which comes from Ministry of Finance, China. It comprises 1,503 firms, among which 1,466 firms are selected for the sample since the other 37 firms did not report the variables of capital or labour. Altogether, 14 variables (see Table 1) are constructed from the data set.

Resource-based firms are defined as firms with either inputs or output that are related to natural resources, namely the mining industry, the production and supply of electricity, gas, and water, and some parts of manufacturing, such as the petrol processing industry, and the steel industry. This criterion is used to construct the dummy variable wrb (resource based).

The dummy variables of firm size (dm and db) are constructed according to the Chinese Standard Classification of Firm Size, which classifies firms by their output and number of employees. A firm with over 2,000 employees and sales of over 300 million RMB and total assets of over 400 million RMB is classified as a big firm, and a firm with employees between 300 and 2,000, sales of 30-300 million RMB, and total assets of 40-400 million RMB is classified as a medium-size firm. For the other variables, the original data set directly reports the data. However, due to the accounting properties in the raw data set, variables such as ete (employee training expenses), rde (R&D expenses), lie (expenses on labor insurance), and ite (expenses on introducing technology) for some firms are reported to be negative, which indicates that the firm is delaying the payment of these variables, and thus a value of zero is set to these variables when they are negative. For the employee training expenses (ete), three firms' values are set to zero; for R&D expenses, one firm's value is set to zero; for the firms' expenses on labour insurance, six firms' values are set to zero; for the firms' expenses on introducing technology, one firm's value is set to zero. The setting of zero is made under the assumption that since the firm did not make the actual payment on these variables, this is equivalent to the firm having zero expenses on these items. Meanwhile this kind of delay in payment will not have a negative effect on technical efficiency.

Descriptive statistics

Table 2-1 gives the descriptive statistics of variables used. From the table, we can see that owing to the fact that the data set covers all kinds of firms in Gansu province, the values of variables used have comparatively large standard deviations compared with the sample average. For example, for output, the average is about 60 million RMB, while the standard deviation is about 736 million RMB, and the maximum value is about 554,794 times of the minimum value! Thus, a subset of the sample is made by extracting firms with output 25 percent above or below the average value. By doing this, we are able to purge potential outliers, however we also impose an artificial restriction. Table 2-2 gives the descriptive statistics of the sub-sample set. We can see that the standard deviations are greatly reduced. The regressions are run with both the total sample and the subset of the total sample. However, the regressions on the sub-sample set will only serve for comparison.

Another point about the data is that for R&D expenses and the expenses on introducing technology, a large proportion of firms reported zero values. For the former variable, 1,370 firms out of the total of 1,466 (93.5 percent) did not have such expenses, and for the latter variable, 1,444 firms out of the total of 1,466 (98.5 percent) did not have such expenses. Thus two types of regressions are made, with and without these two variables.

Empirical results

The estimate is carried out with Frontier 4.1, which is developed by Coelli (1995). Altogether, four models have been estimated on two sets of samples. Table 3 gives results obtained from the full sample set (with a sample size of 1466), and Table 4 presents results obtained from the sub-sample set (with a sample size of 733). And the following interpretation will be based on estimation results over the full sample set (Table 3), and Table 4 will serve as a comparison if necessary.

Table 2-1 Descriptive Statistics for Firms in Gansu Province, China, Whole Sample

Variable	Unit	Average	Stdev	Min	Max
Output	RMB	60,034,756.96	736,239,856.85	48,192	26,736,664,654.24
Capital	RMB	36,950,106.15	363,093,646.91	1,029	12,464,071,257.20
Labour	Persons	298.03	1,346.95	2	31,189.00
Expense on employee training	RMB	39858.38	316463.12	0	8073465.46
R&D expense	RMB	48504.20	716915.13	0	23531354.19
Expense on labour insurance	RMB	573202.64	6493448.48	0	159306895.35
Years of operation	Years	26.81	19.10	1	99
Expense on introducing technology	RMB	3004.46	52262.60	0	1685247.75

Source: Constructed from the data from Ministry of Finance, PRC

Table 2-2 Descriptive Statistics for Firms in Gansu Province, China, Sub-sample Set

Variable	Unit	Average	Stdev	Min	Max
Output	RMB	8,318,116	13,868,720	2,111,879	20,234,057
Capital	RMB	6,435,032	11,658,392	1,029	1.72E+08
Labour	Persons	132.49	174.18	3	1,584
Expense on employee training	RMB	9,416.40	13,872.94	0	145,500
R&D expense	RMB	4,570.85	41,417.44	0	893,070
Expense on labour insurance	RMB	81,309.93	205,846.60	0	1,993,279
Years of operation	Years	26.60	19.27	1	99
Expense on introducing technology	RMB	606.94	6,532.04	0	100,000

Source: Constructed from the data from Ministry of Finance, PRC

Table 3 Estimation Results with Full Sample Set

Variables	Expected sign	Model 1-1		Model 2-1		Model 2-2	
		Coefficient	T	Coefficient	T	Coefficient	T
Constant		13.33	13.69	14.28	24.40	14.39	27.47
Ln Capital	+	0.18	2.60	0.11	2.63	0.09	8.43
Ln Labour	+	0.28*	1.26	-0.03*	-0.24	-0.11*	-1.27
Lnk*lnl		0.01*	0.67	0.03	2.92	0.03	9.29
Resource-based				-0.89	-3.10	-1.11	-7.66
Intercept		1.89	5.72	1.63	5.13	1.48	5.87
Training	-	-1.76E-06	-3.51	-2.04E-06*	-1.69	-2.18E-06*	-1.66
R&D	-	-2.90E-07*	-1.95	-5.18E-08*	-0.41		
Insurance	+	6.69E-08	3.06	6.01E-08	2.74	6.88E-08	5.12
Firm age	+	0.02	2.07	0.02	2.09	0.02	2.63
Square age	-	-1.64E-04*	-1.47	-1.83E-04	-2.11	-2.03E-04	-2.46
Introducing Technology	-	-5.53E-06	-11.44	-4.15E-06	-11.07		
Resource-based		0.16*	1.22	-0.95	-2.32	-1.53	-2.86
FI		-1.06	-2.70	-0.90	-3.16	-0.84	-3.13
Ownership		0.55*	0.85	0.66	2.75	0.71	3.06
Whether big		-0.91	-2.55	-0.91	-3.59	-0.78	-11.88
Whether medium		-0.78	-5.20	-0.92	-6.66	-0.90	-10.47
	γ	0.54	9.22	0.28	6.12	0.43	8.46

Notes: The sample size is 1466; the shaded area is the estimation of production frontier model;
* indicates the coefficient is insignificant at 5% level.
For Model 1-2, Frontier fails to make appropriate estimation, and thus we do not report it to save space.
Source: Estimation by Frontier 4.1 with data constructed from Ministry of Finance, China.

Table 4 Estimation results with sub-sample set

Variables	Expected sign	Model 1-1		Model 2-1		Model 1-2		Model 2-2	
		Coefficient	T	Coefficient	T	Coefficient	T	Coefficient	T
Constant		16.58	30.28	16.29	61.73	16.25	43.89	16.18	53.20
Ln Capital	+	-0.02*	-0.54	0.04	2.31	0.04*	1.51	0.05	2.13
Ln Labour	+	-0.08*	-0.60	0.09*	1.75	0.12*	1.55	0.10*	1.83
Lnk*lnl		0.01*	1.10	-0.01*	-1.43	-0.01*	-1.51	-0.01	-1.93
Resource-based				-0.04*	-1.06			-0.03*	-0.67
Intercept		0.98	8.91	1.27	18.71	1.27	18.86	1.24	17.07
Training	-	-1.18E-05	-3.71	-1.69E-05	-7.54	-1.83E-05	-6.52	-1.80E-05	-6.67
R&D	-	-4.76E-06	-3.62	-1.65E-06*	-1.92				
Insurance	+	-8.82E-07	-2.49	-8.81E-07	-5.18	-1.17E-06	-5.84	-9.14E-07	-4.77
Firm age	+	8.59E-04*	0.24	-1.56E-03*	-0.57	-1.70E-03*	-0.44	1.35E-04*	0.03
Square age	-	-1.18E-05*	-0.27	1.80E-05*	0.46	1.34E-05*	0.30	1.06E-06*	0.02
Introducing Technology	-	-2.05E-05	-2.55	-8.87E-06*	-1.87				
Resource-based		-0.03*	-0.37	-0.17*	-1.00	-0.11*	-1.54	-0.15**	-1.58
FI		-1.02	-4.46	-0.93	-5.32	-1.08	-6.08	-0.92	-5.37
Ownership		0.61	3.19	0.61	3.35	0.69	3.70	0.58	3.02
Whether big		-0.11*	-0.59	-0.27*	-1.83	-0.25*	-1.34	-0.26*	-1.40
Whether medium		-0.19	-2.04	-0.23	-3.33	-0.24	-2.64	-0.23	-2.36
	γ	0.64	5.67	1.00	20984.9	1.00	9539535.4	1.00	36739.1

Note: The sample size is 733;

The shaded area is the estimation of production frontier model;

* indicates the coefficient is insignificant at 5% level.

Source: Estimation by Frontier 4.1 with data constructed from the Ministry of Finance, China.

Production frontier estimates

Table 5 gives the hypothesis test on the production form. It rejects the Cobb-Douglas production form in all four models on both sample sets. Thus, the translog production form is adopted. The shaded areas in both Tables 3 and 4 are the estimates of the translog production frontier model with full sample set and sub-sample set respectively.

Table 5 Hypothesis test

Null Hypothesis	Model	χ^2 statistics	$\chi^2_{0.95}$ value	decision
Whole Sample				
(a) Test for production functional form				
H0: $\beta_3 = 0$ (Cobb-Douglas production form)	M11	22.71	2.7	reject H0
	M12	22.71	2.7	reject H0
	M21	25.06	2.7	reject H0
	M22	25.06	2.7	reject H0
(b) Test for presence of technical inefficiency				
H0: $\gamma = 0$ (no technical inefficiency)	M11	74.41	2.7	reject H0
	M12	-0.43(*)	2.7	
	M21	85.60	2.7	reject H0
	M22	77.88	2.7	reject H0
Sub-Sample				
(a) Test for production functional form				
H0: $\beta_3 = 0$ (Cobb-Douglas production form)	M11	7.03	2.7	reject H0
	M12	7.03	2.7	reject H0
	M21	6.96	2.7	reject H0
	M22	6.96	2.7	reject H0
(b) Test for presence of technical inefficiency				
H0: $\gamma = 0$ (no technical inefficiency)	M11	74.38	2.7	reject H0
	M12	119.88	2.7	reject H0
	M21	126.47	2.7	reject H0
	M22	117.33	2.7	reject H0

Note: The critical values for the hypothesis test are obtained from Table 1 of Kodde and Palm (1986)
(*) Frontier 4.1 stops at iteration 1. This happens because of the data problem.

In four out of the eight estimations, the coefficient of log of labour is negative, however in all four models the coefficient is statistically insignificant, which implies that the number of workers has no obvious impact on firms' production. This may be due to the fact that in Chinese firms, especially in state-owned enterprises, some employees just occupy positions but do not actually do the job. The impact of labour could be better tested if data pertaining to working hours rather than number of workers was available. Unfortunately it is not available.

For capital, the estimations produced a positive and significant coefficient, ranging from 0.09 to 0.18. For the interaction term (lnk×lnl), Model 1-1 reports insignificant estimation, and Model 2-1 and Model 2-2 have significant and positive estimates (both 0.03). The significance of interaction terms in Model 2-1 and Model 2-2 confirms the existence of substitution effect between labour and capital, even though the coefficient of log of labour is insignificant. Meanwhile, we can calculate the elasticity of expected output to capital as 18 percent (Model 1-1), 23.9 percent (Model 2-1, evaluated at the sample average of ln labour), and 21.9 percent (Model 2-2, evaluated at the sample average of ln labour). The estimates of capital elasticity in three models are reasonable as 23.9 percent and 21.9 percent are well within one standard deviation of 18 percent (with standard deviation of seven percent).

Compared with Table 3, the estimates of the capital coefficient and the interaction term in Table 4 are mixed. Model 1-1 has a negative but insignificant estimate of the capital coefficient and a positive but insignificant estimate of the interaction term; Model 2-1 has positive and significant estimate of the capital coefficient and negative but insignificant estimate of the interaction term; Model 1-2 has a positive but insignificant estimate of the capital coefficient, and negative but insignificant estimate of the interaction term; Model 2-2 has a positive and significant estimate of the capital coefficient, and a negative but insignificant estimate of the interaction term. However, even though the sign and significance of the estimated coefficients differ across different models, they are still within one standard deviation of each other.

For the dummy variable, whether the firm is resource-based, the estimates have negative sign, and the magnitude (-0.89 and -1.11 respectively) is significant. However, we are not able to say what the impact will be on its output for a firm that is resource-based, as this variable affects the firm's output via both direct and indirect (through technical efficiency) channels. Compared with Table 3, the sub-sample set's estimate is also negative but insignificant. This comes from the fact that resource-based firms are usually large and have a large output, and while when we constructed the sub-sample set, the firms with output 25 percent above the mean of full sample set were eliminated.

Determinants of technical inefficiency

In the technical inefficiency model, altogether 11 factors have been incorporated. Our major interest focuses on whether the firm is resource-based, whether there is foreign investment in the firm, the ownership, and the firm's size. The hypothesis test on the presence of technical inefficiency (that is, whether $\gamma = 0$) is carried out, and Table 5 gives the results. The hypothesis tests in all four models over both sample sets all reject the null hypothesis of non-existence of technical inefficiency.

We first look at the control variables: the expenditure on employee training, R&D, labor insurance, and introducing technology, and the firm's age. The signs of these variables are all consistent with our expectations. For the employee training expenditure, the coefficient is significant in Model 1-1, but insignificant in Model 1-2 and Model 2-2. Model 1-1 predicts that a 1 million RMB increase of expenditure on employee training will increase a firm's technical efficiency by 1.76 percent. For R&D expenditure, Model 1-1 has significant (at 10 percent significance level) estimate and predicts that 10 million RMB increase of expenditure on R&D will increase a firm's technical efficiency by 2.9 percent; Model 2-1 gets insignificant estimate. For the expenditure on labour insurance, all three models have significant and roughly the same estimate of the coefficient, and predict that 100 million RMB increase of expenditure on insurance will decrease a firm's technical efficiency by 6.69 percent, 6.01 percent, and 6.88 percent respectively. For the expenditure on introducing technology, the coefficient is significant, and introducing one million RMB of technology will promote a firm's technical efficiency by 5.53 percent (Model 1-1) or 4.15 percent (Model 2-1). Comparing the technical efficiency improving effect of the expenditure on employee training, R&D, and introducing technology, we can find that introducing technology is the lowest cost way to improve the technical efficiency, given all other factors held constant. For firm's age, it does display a quadratic relationship with technical efficiency (except in Model 1-1, the quadratic term is insignificant).

As for the effect on technical efficiency of a firm being resource-based, Model 1-1 reports a positive but insignificant estimate, and both Model 2-1 and Model 2-2 report negative and significant estimates. Since Model 1-1 has a different estimate from Model 2-1 and Model 2-2, we can conduct a hypothesis test to decide which is more appropriate. The likelihood ratio test is made between Model 1-1 and Model 2-1, with a null hypothesis that Model 1-1 is appropriate (i.e. the coefficient of whether resource-based is equal to zero in the production function), and the test statistic is 21.9, bigger than the critical value (2.7) at five percent significance level. Thus we reject the null, and can conclude that firms that are resource-based achieved more technical efficiency than non-resource-based firms after controlling for other factors such as R&D expenses. Moreover, the estimates of Model 1-2 and Model 2-2 predict that, everything else being equal, resource-based firms on average are 0.95 percent or 1.53 percent more technically efficient than non-resource-based firms. This kind of technical efficiency may come from the benefit of agglomeration or from comparative advantage, but it is insufficient for us to distinguish between them in the model.

The findings indicate that foreign investment has a positive effect on firms' technical efficiency since the coefficients are all negative and significant. This point is consistent with the idea that foreign investment, particularly foreign direct investment, generally brings in comparatively advanced technology and management experience, which helps to increase firms' technical efficiency. The magnitude of this coefficient is estimated to be around -1, and all the estimates are consistent with each other in the sense that the coefficient of one estimate is within one standard deviation interval of other estimates. Compared with estimation over the full sample set, the estimation over the sub-sample set produces very similar results.

On the effect of ownership (that is, whether or not the firm is privately owned) on technical efficiency, the coefficient estimated is positive and significant (except in Model 1-1), and as stated before, the hypothesis test rejects Model 1-1 in favour of Model 1-2. So we can conclude that ownership plays a role in firms' technical efficiency, and on average publicly owned firms (state-owned, collective-owned and joint-stock companies in which the government dominates) are 0.66 percent (or 0.71 percent) more technically efficient than privately owned firms (that is, ownership=1) after controlling for other factors. This result may be due to the fact that the scale of business of private firms is small and their technology level is comparatively low. Especially in Gansu, a province where private firms are still not well developed and the institutions for private business (for example, the regulation or registration of businesses, and taxation) are not overly supportive of private business, private firms may perform worse than public firms which continue to get support from the local government. Besides, firms in Gansu province are more likely to be related to the resource industry owing to its natural endowment. And the start-up standard in the resource industry usually will be higher (for example, more start-up investment is needed). This prevents private agents entering this kind of industry. However, we should note that this does not mean the overall efficiency of private firms is lower than that of public firms, since here only technical efficiency is measured.

On the effect of firm size on technical efficiency, the estimation results show that compared with small firms, both the medium-sized and large firms operate more technically efficiently on average. It indicates that big firms are more capable of developing their technology and using technology more efficiently. The coefficient for db (whether the firm is big) is -0.91 or -0.78, which shows that big firms are on average 0.91 percent or 0.78 percent more technically efficient than small firms. The coefficient for dm (whether the firm is medium-sized) is -0.92 or -0.9, which shows that medium-sized firms are 0.92 percent or 0.9 percent more technically efficient than small firms. Compared with large firms, medium-sized firms are a little bit more technically efficient. This demonstrates that firm size does affect technical efficiency, which may be because resource-based firms usually have larger start-up costs (larger size). For the estimates over the sub sample set, the signs are all consistent, except the coefficient for db is insignificant, which happens again because of the methods we used to construct the sub-sample data set.

Mean technical efficiency estimate

Table 6 gives the descriptive statistics for the estimate of the technical efficiency in eight models with different sample sizes, and Figures 3 and 4 present the cumulative distribution function of firms' technical efficiency. In the full sample set, the estimates of mean technical efficiency are averaged around 27 percent, ranging from 20 percent to 33 percent. The estimates of the mean technical efficiency here are a little bit lower compared with mean technical efficiency level of 50-70 percent that is usually obtained in other studies on technical efficiency in China. In contrast, the estimate of mean technical efficiency in the sub-sample set is higher than that of whole sample set, averaging roughly 41 percent. This indicates that firms that are not included in the sub-sample are less technically efficient than firms in the sub-sample on average, since the inclusion of these firms in the whole sample set sufficiently lowers the estimate of mean technical efficiency.

Table 6 Estimates of mean technical efficiency (%)

	Model 1-1		Model 1-2		Model 2-1		Model 2-2	
	Full	Sub		Sub	Full	Sub	Full	Sub
Mean	20.03	48.48		41.25	28.94	41.07	32.67	41.03
Median	15.64	45.78		34.14	25.67	34.47	29.25	34.46
Maximum	89.77	94.37		99.99	90.63	99.91	90.79	99.99
Minimum	1.41	18.55		10.41	3.30	10.35	4.18	10.22
Std. Dev.	14.58	17.82		24.24	16.42	24.05	17.83	24.08

Source: Estimated by Frontier 4.1 with data constructed from the Ministry of Finance, China.

Figure 3. Empirical CDF for technical efficiency estimate with whole sample

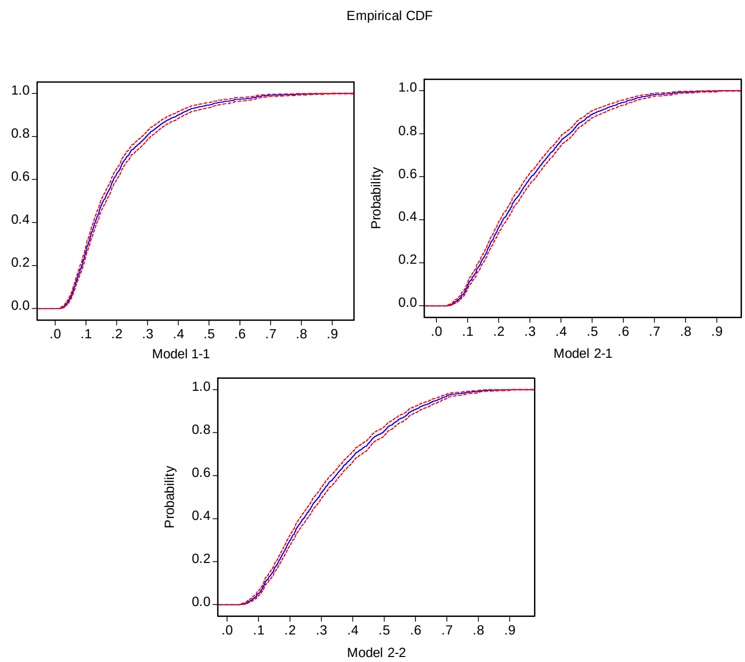
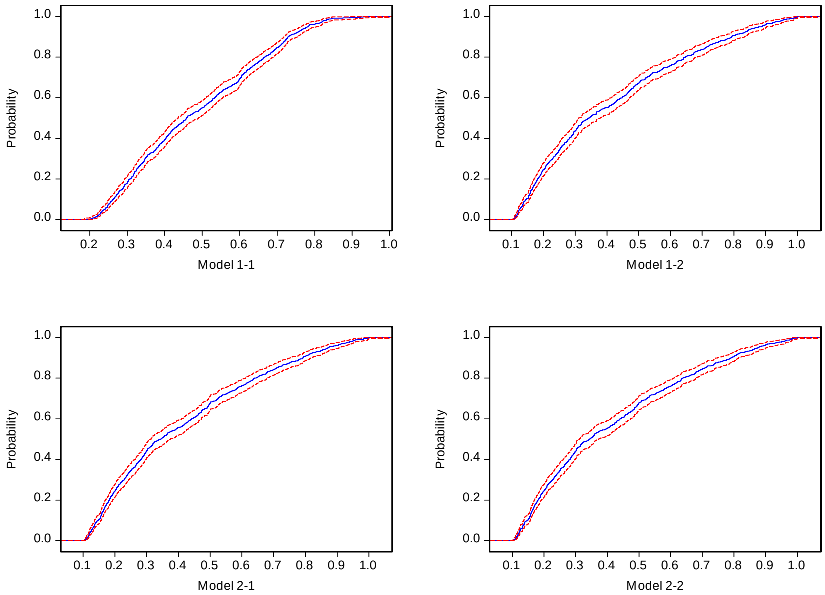


Figure 4. Empirical CDF for technical efficiency estimate with sub-sample



Conclusion

This paper used the stochastic production frontier model and a technical inefficiency model to analyse the technical efficiency of firms in Gansu province, China. Compared with previous studies, this paper focused on a province instead of an industry. This is the major characteristic of this study.

In the empirical estimation of technical efficiency determinants, altogether four models are estimated over two sample sets. The findings include: first resource-based firms on average are more technically efficient than non-resource-based firms; second, foreign investment is beneficial to the improvement of technical efficiency; third, the ownership of firms seems not to play a role in firms' technical efficiency; fourth, bigger firms tend to operate more technically efficiently than smaller firms.

It also should be noted that although the study indicates that resource-based firms are more technically efficient than non-resource-based firms, the study doesn't cover the ways in which this happens. For example, we find resource-based firms are more technically efficient than non-resource-based firms, but we can't determine whether this happens due to agglomeration benefit or comparative advantage. This shall be left in further study.

In the empirical estimation of mean technical efficiency, the scale obtained in Gansu province is rather low compared with other studies on Chinese industries. However, this also shows that there is a substantial room for firms to increase their technical efficiency. With the aim of improving the technical efficiency of firms, some policy implications can be drawn from the above analysis. First, since foreign investment is beneficial to the improvement of technical efficiency, the government should encourage more foreign investment, especially foreign direct investment, to flow into the province. The openness to foreign capital is likely to benefit firms' performance. Second, since private firms are not operating more technically efficiently than public firms, privatisation will not necessarily result in an improvement of technical efficiency. Thus it is not necessarily a good way to improve firms' technical efficiency. Instead, since private firms are being discriminated against, policies aiming at providing a fair competition environment might improve their technical efficiency. Third, to encourage the formation of big firms may be a good approach to improve firms' technical efficiency, since the empirical results show that the larger the firm is, the more technically efficient it is.

References

Aigner, D.J., C.A.K. Lovell, and P.J. Schmidt, 1977. 'Formulation and estimation of stochastic frontier models', Journal of Econometrics 6(1):21-37.

Bhattacharyya, A., and E. Parker, 1999. 'Labor productivity and migration in Chinese agriculture: a stochastic frontier approach', China Economic Review, 10:59-74.

Carter C.A., and A.J. Estrin, 2001. 'Market reforms versus structural reforms in rural China', Journal of Comparative Economics, 29:527-541.

Cheng, E.J., 1998. 'Household heads, non-economic factors & grain production in China in the 1990s', Working Paper #98/5, Center for Asian Studies, Chinese Economy Research Unit, University of Adelaide, Adelaide.

Coelli, T., 1996. 'A guide to Frontier Version 4.1: a computer program for stochastic frontier production and cost function estimation', CEPA Working Paper, University of New England, Armidale, Australia.

Coelli, Tim, D.S. Prasada Rao, and George E. Battese, 1998. An Introduction to Efficiency and Productivity Analysis, Kluwer Academic Publication, London.

Démurger, Sylvie, J. D. Sachs, W. T. Woo, S. Bao, G. Chang, and A. Mellinger, 2002. 'Geography, Economic Policy, and Regional Development in China', Asian Economic Papers, 1(1):46-197.

Dong, X.Y., and L. Putterman, 1997. 'Productivity and organization in China's rural industries: a stochastic frontier analysis', Journal of Comparative Economics, 24:181-201.

Fleisher, B.M., and Y.H. Liu, 'Economies of scale, plot size, human-capital, and productivity in Chinese agriculture', Quarterly Review of Economics and Finance, 32:112-123.

Forsund, F.R., C.A.K Lovell, and P. Schmidt, 1980. 'A survey of frontier production functions and of their relationship to efficiency measurement', Journal of Econometrics 13:5-25.

Golley, J., 2003. 'Location and Industrial Location and Regional Development', in R. Garnaut and L. Song (eds), China: New Engine for World Growth, Asia Pacific Press, Canberra.

Huang, Y., and K.P. Kalirajan, 1997. 'Potential of China's grain production: evidence from the household data', Agricultural Economics, 17:191-199.

Jefferson, G..H., 1990. 'China's Iron and Steel Industry Sources of Enterprise Efficiency and the Impact of Reform', Journal of Development Economics, 33:329-355.

Kong, X., R.E.Marks, and G.H. Wan, 1999. 'Technical efficiency, technological change and total factor productivity growth in Chinese state-owned enterprises in the early 1990s', Asian Economic Journal, 9:276-281.

Konmpas, T., T.N. Che, and R.Q. Grafton, 2004. 'Technical efficiency effects of input controls: evidence from Australia's Banana Prawn Fishery', Applied Economics, 36:1631-1641.

Kumbhakar, S.C., and C.A.K. Lovell, 2000. Stochastic Frontier Analysis, Cambridge University Press, London.

Liu, Z., and J. Zhuang, 2000. 'Determinants of technical efficiency in post-collective Chinese agriculture: evidence from farm-level data', Journal of Comparative Economics 28:545-564.

Movshuk, O., 2004. ‘Restructuring, productivity and technical efficiency in China's iron and steel industry, 1988-2000’, Journal of Asian Economics, 15:135-152.

Tong, C.S.P., 1999. ‘Production efficiency and its spatial disparity across China's TVEs A stochastic production frontier approach’, Journal of Asian Economics 10:415-430.

Wan, G.H., and E.J. Cheng, 2001. ‘Effects of land fragmentation and returns to scale in the Chinese farming sector’, Applied Economics, 33:183-194.

Wang, J., G. L. Cramer, and E.J. Wailes, 1996. ‘Production efficiency of Chinese agriculture: evidence from rural household survey data’, Agricultural Economics, 15:17-28.

Wu, Yanrui, 1995. ‘The productive efficiency of Chinese iron and steel firms, Resources Policy, 21(3):215-222.

Xu, X., and S.R. Jeffrey, 1998. ‘Efficiency and technical progress in traditional and modern agriculture: evidence from rice production in China’, Agricultural Economics, 18:157-165.

Zhang, A., Y. Zhang, and R. Zhao, 2003. ‘A study of the R&D efficiency and productivity of Chinese firms’, Journal of Comparative Economics, 31:444-464.

Notes

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1 The author would like to thank Dr. Jane Golley, School of Economics, The Australian National University, for her comments and suggestions. Any errors are the author’s.

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3 A cross-sectional version is made from Batttese and Coelli’s original version for panel data.

4 Here, Frontier 4.1 (Coelli 1996) is used to estimate equation (1) and (2).