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Measuring the True Technical Efficiency of Farmers' Forest Management in Fujian, China: A Three-stage Dea Analysis

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Abstract: Technical efficiency of farmers' forest management is the core issue of forestry development. This study applied three-stage data envelopment analysis model to evaluate the technical efficiency, pure technical and scale technical of farmers' forest management, excluding the impact of environmental effect and statistical noise. Questionnaires were collected and analyzed from 700 heads of households in Fujian, China. The results from the first-stage indicated that overall efficiency were low. In addition, the environmental variables had significant effect on the technical efficiency such as financial subsidies and farmer's technological level through stochastic frontier analysis. After the adjustment of environmental variables and statistical noise, the average technical efficiency in the third-stage DEA improve significantly than the first stage. The results also indicated that nearly half of farmers had capital and labor input slack. Therefore, our findings suggest that increasing farmers' financial subsidies, introducing advanced technology and expanding scale of production should be take into consideration to improve technical efficiency.

Key words: Farmers' forest management, technical efficiency, environmental effect, three-stage DEA

INTRODUCTION

Since, 2003, a new round of collective forest tenure reforms has been sweeping across rural China (Xu, 2010). First time forest owners took the forefront as forestry managers because they are essential in natural resource management. After the collective forest tenure reform, how to strengthen forest resources management, how to evaluate the efficiency of farmer's forest management reasonable, how to improve management level and how to increase the revenue of forestry farmers as well as their cooperative organizations have become key issues which may influence the reform effect and sustainability.

Having received considerable attention in past decades, numerous studys and books introduce the basic methodology of DEA and it has been widely implemented in different parts of the world, national scholars have begun to evaluate the efficiency of forest management (Kao and Yang, 1991; Sowlati, 2005). The first applied the DEA approach to explore the efficient. Kao and Yang (1991) evaluated the relative efficiency of 13 forest district in Taiwan and discuss that there are several important inputs and outputs to consider in evaluating the efficiency of multiple-use forest. However, they ignored a careful examination discloses that several basic assumptions imposed by the DEA. Nyrud and Baardsen (2003) used DEA to examine the production efficiency of Norwegian sawmills and concluded that mills staying in business for a long time were relatively more efficient and average productivity growth for sawmills was low.

Studies on the managerial efficiency of farmers' agriculture and forest management are mostly focus on understanding farmers' operating efficiency and the factors affecting such efficiency. The major weakness in these previous studies is that the common frontier is built by pooling all farmers and measuring efficiency differences between different farmers without considering environmental conditions.

Hence, based on the previous researches, the true technical efficiency obtained by the three-stage Data Envelopment Analysis (DEA) model with consideration of environmental variables and statistical noise. The findings can help farmers understand the real causes of poor technical efficiency and make improvements accordingly. Therefore, our study will also help policy makers to make some favor policy to improve the efficiency of farmers' forest management as well as offer management a reference for the assessment of their technical efficiency.

MATERIALS AND METHODS

Methods: Data Envelopment Analysis (DEA) is a nonparametric method for measuring the efficiency of a Decision-Making Unit (DMU). Any group of entities that

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receives the same set of the inputs and produces the same set of outputs could be designated as a DMU. The study applies the three-stage DEA approach proposed by Fried *et al.* (2002).

In the first stage, the Initial DEA Producer Performance Evaluation, BBC model assumes Variable Returns to Scale (VRS).We assumed that there are n DMUs, each DMU has m inputs and s outputs as well. The inputs set as $X_j = (X_{1j}, X_{2j}, \ldots, X_{mj})^T$ and inputs set as $Y_j = (y_{1j}, y_{2j}, \ldots, y_{sj})^T$, where j = 1,2...,n and $x_{ij}>0$ is the of jth DMU, $y_j>0$:

$$
DBCC\begin{cases} \sum_{j=1}^{n} {}^{\min\theta} X_j\lambda_j + S^+ = \theta X_0 \\ \sum_{j=1}^{n} Y_j\lambda_j - S- = Y_0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \geq 0, j = 1,2,\ldots,n, \theta \text{unconstricted} S- \geq 0, S^+ \geq 0 \end{cases}
$$

where, λ_j is intensity variables, θ is the relative TE of DMU_0. S^+ is the slack variable of the total inputs and S^- is the slack variable of the total outputs. When $\theta = 1$ and $S^+ = S^- = 0$, DMU_0 is efficient; when $\theta = 1$ and $S^+ \neq 0$, or $S^- \neq 0$, DEA_0 is weak efficient; when $\theta<1$, DEA_0 is not efficient. Furthermore, θ is Technical Efficiency (TE) that can divided into Pure Technical efficiency (PTE) and Scale Efficiency (SE).

In the second stage, the slack variables in the first stage are integrated into and adjusted in accordance with the original inputs. Since, the DEA model here is set as an input orientation model, At this stage, regression analysis can be conducted with the stochastic frontier approach to adjust the uncontrollable factors, that is, the total input slack of the items, S_{ni}, is the dependent variable in the SFA regression model:

$$
s_{ni} = f^n(z_i; \beta^n) + v_{ni} + u_{ni}, n = 1, 2, \ldots, N,\ i = 1, 2, \ldots, I
$$

where, i = 1, 2,…, I; s_{ni} is the nth input slack of ith DMU. Assuming K observable environmental variable, $z_i = [z_{1i}, z_{2i}, \ldots, x_{ki}]$,where $f^n(z_i; \beta^n)$ is the deterministic feasible slack frontier and as general $f^n(z_i, \beta^n) = z_{ni}\beta^n$, β^n is the environmental factor parameter vector for estimation; the composite error $(v_{ni}+u_{ni})$ is the residual; $v_{ni} \sim N(0, \sigma_{vn}^2)$ is statistical noise and $u_{ni} \sim N^+(u^n, \sigma_{un}^2)$ refer to the managerial inefficiencies; v_{ni} and u_{ni} are independent and unrelated. In particular, as:

$$
\gamma = \frac{\sigma_{vn}^2}{\sigma_{vn}^2 + \sigma_{vn}^2} \rightarrow 1
$$

the impact of managerial inefficiency dominates that of statistical noise in the determination of slack in usage of the nth input, while just the opposite occurs as:

$$
\gamma = \frac{\sigma_{vn}^2}{\sigma_{un}^2 + \sigma_{vn}^2} \rightarrow 0
$$

In order to adjust the initial inputs and obtain estimates of $\hat{v}_{ni}$ for each producer, the Jondrow et al. (1982) methodology was used to decomposes the composed error terms in equation. From the conditional estimators for managerial inefficiency given by:

$$
\widehat{E}[u_{ni} | v_{ni} + u_{ni}]
$$

derived estimators for statistical noise residually by means of :

$$
\widehat{E}[v_{ni} | v_{ni} + u_{ni}] = S_{ni} - z_i\hat{\beta}^n - \widehat{E}[u_{ni} | v_{ni} + u_{ni}] = 1, 2, \ldots, I
$$

n = 1, 2, …, I

Then, adjusted inputs are constructed from the results of the Stage 2 SFA regressions by means of:

$$
\hat{x}_{ni} = x_{ni} + \left[\max_i\left\{z_i\hat{\beta}^n\right\} - z_i\hat{\beta}^n\right] + \left[\max_i\left\{\hat{v}_{ni}\right\} - \hat{v}_{ni}\right], n = 1, 2, \ldots N; \\ i = 1, 2, \ldots, I
$$

Where $\hat{x}_{ni}$ and x_{ni} are adjusted and observed input quantities, respectively. Parameters $\hat{\beta}^n$ is estimator for environment. The:

$$
\max_i\left\{z_i\hat{\beta}^n\right\} - z_i\hat{\beta}^n
$$

puts all producers into a common operating environment, the least favorable environment observed in the sample. The:

$$
\max_i\{\hat{v}_{ni}\} - \hat{v}_{ni}
$$

puts all producers into a common state of nature, the unluckiest situation encountered in the sample. These adjustments vary both across producers and across inputs.

Stage 3 is re-evaluating DMU whose input date x_{ni} have been revised $\hat{x}_{ni}$ and the same outputs y_{ni} by input BCC model mentioned in stage 1.The result is without environmental variables and statistical noise for the TE,PTE and SE.

Date collection: The study was based on primary cross-sectional data collected using stratified random sampling. 7 villages provided by the local Forest Administration in Sanming where is rich in forestry resources, yielding 700 participated farmers in total. The surveyed farmers completed the questionnaire in the villages with the help of the investigators from July 2012 until July 2013 by a research team. In the survey, obtained as much information related to farmers' forest management as possible. Of the distributed questionnaires, 670 (95.71% of the response rate) were returned that were correctly filled out and the data were analyzed by SPSS 19.0.

Input and output measure index: Due forest management can have dozens of distinct inputs and outputs. The study here measuring index draws as OECD guided (OECD Manual, 2001) and used a real discount rate of 7%, similar to the rate previously utilized for comparing systems (Frey *et al*., 2012).

Inputs: Capital input in recent five years (including forest land use fee, seedlings fee, pesticide and fertilizer use fee); Labor in person-days (afforestation, Young forest tending, stand improvement protecting forests); China Fir area and Moso bamboo area.

Considering the price of wood is uncontrolled, future output of timber by using growth and yield models calibrated to current stand measurements with Ri,chard Equation $Y = A^* [1\text{-exp}(-kt)]^c$, where Y is kind of tree, t is year, A, k, c is parameters and the stand volume equations of (Zang, 2006) to estimate the stand volume of China Fir in Fujian province:

$$M = 460.5863^* [1\text{-exp}(0.082905t)]^{3.098856}$$

where, M is the stand volume of per hectare, t is year. Because the production rate of China Fir is usually keep percentage on 70%, here $V = 0.7^*M$ (timber output per hectare). In addition, the Bamboo yield mainly use the farmers in the bamboo forest land production products. Table 1shows the descriptive statistics of the respective input and output variables.

Environment variable: Environment variable is described those factors which may affect the efficiency of farmer's forest management. Generally, they are not different from the traditional inputs and uncontrollable by farmers themselves (Fried *et al*., 2002). It included macroeconomic environment, local financial subsides on forest development, farmer's education level and forest management technology level. Since farmers' income level had positive effect on forest management so as to improve the efficiency of their forest management. Forestry income of household measured. Sound policies of the government in the forestry will be favor to farmers' forest intervention by increasing their expectations. Thus, ecological forest subsidies and afforestation subsidies was chose as measure index. The improvement of farmers' cultural level can not only increases their accumulation of knowledge and skills to effective economic decisions, but also is an essential factor to participate in cooperative organizations. According to Wang and Yao (2003), chose educational year to measure. Farmer with advanced technology can motivate the diffusion of new technology and improve the efficiency of their management, so chose the participation in technological training supported local forestry management department to measure.

Table 1: Descriptive the efficiency measure index and statistical characteristics of farmers' forest management

	Variables	MIN.	MAX.	MEAN	SD
Input	Capital(yuan)	0	120000	4453.34	20800.6
	Labor (man/day)	0	3000	161.58	537.66
	China fir area (mu)	0	826	84.05	207.03
	Moso bamboo area (mu)	0	300	19.70	59.170
Output	Timber (m^3)	0	138346	7636.96	25576.73
	Moso bamboo yield (yuan)	0	82617	2909.09	14368.27

RESULTS

Outcome of the first stage traditional DEA: In the first-stage DEA, MAXDEA 6.0 software analyzed efficiency level their TE, PTE and SE. As Table 2 showed, TE1 was 0.115, PTE1 was 0.367 and SE1 was 0.313. In other words, 89.5% of the production factors resulted in waste. Based on the first-stage DEA results, the technical inefficiency was both caused by PTE1 and SE1; Moreover, 95.9% farmers' TE1 were below 0.3, 77.8% farmers' PTE1 is below 0.3 and 84.9% farmers' SE1 is below 0.3. Therefore, the farmers were not operating under the optimal scale resulted in the waste of production factors.

Outcome of the second stage of Stochastic Frontier Approach (SFA) regression: By employed Frontier 4.1 software, the input slacks can be drawn from first stage empirical results as dependent variable of Stochastic Frontier Approach (SFA) model, Forestry income of household, local forest financial subsides, farmer's educational year and farmer's participation in technological training as independent variables. While there also had statistical noise on input slack variables. Adjusting uncontrollable factors through the SFA, the regression analysis was conducted to find the influence of four environmental variables.

Table 2: Efficiency of farmers' forest management distribution in different sore scale

	Scale					
Efficiency	0-0.1	0.1-0.2	0.2-0.3	0.3-0.6	0.6-0.9	1
TE1	445	146	52	13	6	8
PTE1	347	83	91	84	35	30
SE1	386	138	45	58	30	13

TE1 is average technical efficiency in stage-1, PTE1 is average pure technical efficiency in stage-1and SE1 is average scale efficiency in stage-1 (TE1=PTE1*SE1)

Table 3: Stochastic frontier estimation results

	Dependent variable			
Independent variable	LIS	CIS	CFAIS	MBAIS
Constant	0.914	2.887	1.260	0.411
Standard errors	1.292	2.897	3.086	2.04E+00
Forest income	0.182	0.355	0.012	-0.141
Standard errors	0.149	0.299	0.161	0.306
Financial subsidies	- 0.745*	0.587*	0.364	0.821
Standard errors	0.528	0.236	0.196	0.483
Educational level	0.201	0.718	7.25E-01	1.292
Standard errors	0.487	0.435	8.94E-01	1.023
Technological training	-1.316***	-1.676*	0.903	0.418
Standard errors	0.292	1.962	0.808	0.937
σ2	0.347***	2.838***	0.103*	0.453***
Standard errors	0.062	4.29E-01	0.048	0.117
γ	6.13E-06	0.999***	1.722E-06*	6.96E-06*
Atandard errors	1.166E-02	8.92E-05	3.33E-02	1.59E-02
log likelihood function	-5.51E+01	-5.88E+01	-2.53E+00	-29.68
LR test of the one-sided error		1.59E+01		

*,**,***Significant at the 10, 5, 1% level, respectively, LIS: Labor input slack, CIS: Capital input slack, CFAIS: China Fir area input slack, MBAIS: Moso bamboo area input slack

Table 4: Outcome of the third stage DEA and inputs slacks

TE3	PTE3	SE3	Input	Slack	Amount	Average of slack
0.167	0.573	0.291	Capital (yuan)	Yes	306	80.714
				No	364	
			Labor	Yes	290	15639.65
			(man/day)	No	380	
			China fir area	Yes	36	2.074
			(mu)	No	634	
			Moso bamboo	Yes	122	11.6
			area (mu)	No	548	

From Table 3, this finding indicated that the value of γ of capital regression equation was close to 1 at 1% significance level, so the management inefficiency is the dominant role. And since the value of ã of the China Fir size and Moso bamboo size regression equation were both close to 0 at 10% significant level, there were no management influence on China Fir input and Moso bamboo input but statistical noise. Therefore, it was necessary to strip the management inefficient and statistical noise through SFA regression.

Furthermore, due to some regression coefficient cannot through the test of significance and just had the direct guide meaning, they did not be considered here, such as the forest income of household and educational level. The financial subsidy has significant positive affect on labor input slack but negative impact on capital input slack. That is to say, as amount of financial subsidies increase, more capital input waste, which may be cause by subsidies would increase farmers' expectation on income and encourage farmers to expand scale of planting while invested capital blindly. But farmers would reduce waste on labor input by financial subsidies increasing, which may result from stimulating farmer effective management. The participation in technological training had significant positive effect on labor and capital input slack. The higher technological level of farmers on forest management make farmer more positive to engage in forest management and improve their management efficiency. Generally, farmers who could understand advanced technology with better management experience and invest capital and labor efficient as well.

Outcome of the third stage of DEA model: After the adjustment of the uncontrollable factors during the second stage, the study re-calculates the true technical efficiency of the farmers' forest management in the third stage. Conducted adjusted replaced original inputs and keep the original outputs with input-BCC model. Table 4 showed that, the TE3 was 0.167, PTE3 was 0.573 and SE was 0.291 under the third-stage DEA estimate. In other words, 83.3% of the production factors resulted in waste. In comparison, the results of the first stage DEA (Tab.2), after adjusted the environmental effects and statistical noise, TE3, PTE3 and SE3 is 0.167, 0.573 and 0.291,respectively. Both TE3 and PE3 had much higher than TE1 and PE1, but SE3 have decreased. The reason of increase of the average of pure technical efficiency was that those farmers were in a relative worse environment and had a bad luck in forest management.

According to Table 4, the finding indicated the amount of each input slacks. Nearly half of farmers had CIS (45.67%) and LIS (43.28%). This were result from a large amount of resource waste in forest produce and management. Only 5.37% of farmers had CFAIS and 18.21% of farmers had MBAIS. Both were small which illustrated that famers positively utilized the forestland more effective than before, as they felt they became the true owners after collective forest tenure reform.

CONCLUSION

This study uses the first-stage and third-stage DEA approach to measure the TE of 700 farmers' forest management. The results indicated that the major cause of management inefficiency are scale inefficiency and pure technical, namely, the waste of production resources brought about by not product at the optimal scale.

Moreover, the farmer's forest income and educational level were not significant impact on the efficiency but still important as direct guide. After adjustment of environmental effect and statistical noise, the average TE in the third-stage DEA improve significantly than the first stage. This finding suggests that the government should make some innovation to expand the scale of production. Meanwhile, some useful policy also on increasing financial subsidies, introducing new and advanced technology into forest management to reduce the capital and labor input slack in the process of production investment should be considered.

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