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Measurement of Agricultural Production Efficiency and the Determinants in China Based on a DEA Approach: A Case Study of 99 Farms from Hebei Province

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Using an input–oriented DEA model with the assumption of VRS, this paper develops a framework on agricultural production efficiency including 2 outputs and 6 inputs. The data source is a survey to 99 household farms of Hebei province, China, conducted by the authors in 2010. According to the efficiency scores of DEA, the sampled farms are divided into three types, and the status of returns to scale for each farm is examined as well. Slack analysis of the outputs shows that comparing with net profit, ratio of net profit can be increased with a larger margin. Meanwhile, the radial and slack adjustments indicate the inefficient and redundant amounts of the inputs, respectively. In the second stage, effects of a variety of social and natural determinants are assessed, with the adoption of an Ordinal Logistic Regression model. Based on the empirical findings, policy recommendations are put forward, concerning the circulation of basic agricultural factors of land, labor, etc.; strengthening the construction of public agricultural infrastructures, particularly the irrigation facilities; deepening the institutional reforms to extend quality seeds and advanced agricultural technologies; and the closer integration of the public services and credit markets supporting the agriculture.

Key words: Agricultural Production Efficiency, China, DEA, Household Farm

INTRODUCTION

Being the largest developing country, China needs sufficient and safe supplication of agricultural products, due to the increasing population, diminishing arable land and limited irrigating water (P. Chen, *et al*., 2008). Moreover, efficient agricultural production constitutes foundation for the supply of sufficient food stuff and transfer of rural labors, thus supporting the development of national economy. Therefore, Chinese agricultural productivity has become a popular topic amongst researchers over the latest years (John M., *et al*., 1989; P. Chen, *et al*., 2008; Z. Chen, *et al*., 2009; Daniel C. M., *et al*., 2010).

Since the pioneering work of Farrell (1957), many studies have been devoted to estimate production efficiency. Generally, they are categorized into two approaches: the parametric functions symbolized by Stochastic Frontier Production (SFP, Aigner, *et al*., 1977), and the nonparametric Data Envelopment Analysis (DEA) (Charnes, *et al*., 1978). Both methods estimate the efficiency frontier, which it is considered as the best performance observed among the firms, and being referred to calculate the other firms' relative efficiency. The main strengths of the SFP are that it deals with stochastic noise and permits statistical tests of hypotheses, pertaining to production structure and degree of inefficiency. Meanwhile, the requirement of a specified frontier production function constrains its applicability. By contrast, using linear programming to construct a piece–wise frontier that envelops observations of all firms, DEA embraces the advantages that being capable of bearing multiple inputs and outputs in different units of measurement. Moreover, DEA avoids the parametric specification of technology and the distributional assumption for the inefficiency terms, and it does not claim the weights on different inputs and outputs as well (Coelli, *et al*., 2005).

In agricultural production, a variety of inputting elements, including land, labor, fertilizer, water, etc., are used, of which the absolute and relative revenues are to be measured. Meanwhile, the variables are usually with different units, making it difficult to assume the parameters accurately. Thus a multiple quantitative model of DEA is appropriate for the measurement of agricultural production efficiency. At the same time, what the farmers can really control is the quantity of inputs, rather than the outputs. Moreover, due to natural and marketing risks, changing governmental regulations, financial constraints, etc., farms cannot be operated at optimal scales all the time. There are two orientations in DEA: input–oriented models seek to save the inputs, with outputs hold constant, while output–oriented models aim to increase the outputs, with inputs keep fixed. As to assuming the returns to scale, Constant Return to Scale (CRS) is appropriate when all firms are operating at optimal scales, while Variable Return to Scale (VRS) without

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this limitation. Therefore, an input–oriented DEA model with the assumption of VRS is adopted in this study, as in DEA, one should select the orientation according to which quantities the managers have most control over (Coelli, *et al*., 2005). In the second stage, an ordinal logistic regression model is adopted, to explore effects of the social–natural determinants on the production efficiencies (A. Uzmay, *et al*., 2009; Maria P., *et al*., 2010).

A brief literature review on production efficiency measurement of Chinese agriculture shows that, there are still topics need to be researched with further depth. (1) As agricultural development is heavily influenced by external environment, it is necessary to assess not only production efficiency, but also effects of the social and natural factors. Although some papers, such as Daniel C. M., *et al*. (2010), conducted two–stage analyses, much more studies targeted only on measurement of Chinese agricultural efficiency, without modeling the effects of natural and social determinants in the second stage. (2) Because household farm is the basic and overwhelming managerial unit of Chinese agriculture, much more researches based on farm surveys should be conducted, to capture information from the micro–level perspectives (S. Tan, *et al*., 2010). According to Carter, *et al*. (2003), estimates derived by aggregate and individual data may lead to different conclusions and policy implications. However, many of the previous studies are based on second–hand aggregate datasets, especially the statistics of provincial regions. Z. Chen, *et al*. (2009) evaluated technology and technical efficiency of Chinese farms, based on the farms survey conducted by China Ministry of Agriculture over 1995–1999, with the whole country being grouped in four regions. H. Dong, *et al*. (2010) measured the agricultural efficiency of the 31 Chinese provincial–level regions in 2008. (3) Some studies focused on the measurement of production efficiency of one certain agricultural product (Y. Lu, *et al*., 2009; Y. Liu, *et al*., 2010), leaving many open research topics upon the overall efficiency evaluation of all the crops grown within individual farms. (4) Within DEA model, attributes of inputs, outputs and efficiency sores should be explored, both in different grouped farms and aggregate analysis of total farms, rather than describe the general characteristics as put in most of the previous studies.

Therefore, we intend to fulfill the following targets in this paper: (1) formulating a DEA model appropriate to analyze agricultural production efficiency, taking Chinese household farms as the DMUs, (2) revealing the overall attributes of agricultural production efficiencies in each type of farms, (3) finding out theoretical margins for the increasing of outputs and saving of inputs, (4) identifying the significant social and natural factors that affecting the agricultural production efficiency, through the application of ordinal logistic regression, and (5) putting forward policy recommendations in the last section.

THEORETICAL FRAMEWORK OF DEA

The basic model

DEA includes a variety of linear programming procedures, in which a non–parametric frontier is constructed over the data, and efficiencies of the DMUs are measured relative to this surface (Coelli, *et al*., 2005). Charnes, *et al*. (1978) proposed an input–oriented model with the assumption of CRS, based on which Banker, *et al*. (1984) included the situations of VRS by adding the constraint of I1' λ=1:

$$\begin{aligned} &\underset{\theta_i,\ \lambda_i}{Min}\,\theta_i \\ &st.\ -y_i+Y\lambda_i \geq 0, \\ &\quad \theta_i x_i - X\lambda_i \geq 0, \qquad (i=1, 2, \ldots, n) \\ &\quad \mathrm{I1'}\lambda_i = 1, \\ &\quad \lambda_i \geq 0,\ 0 \leq \theta_i \leq 1 \end{aligned} \tag{1}$$

where Y and X are the output and input matrix, y_i and x_i are the output and input for the i–th firm, respectively. λ_i is an $n\times 1$ vector, serving as a weight system to each firm and thus form a optimal combination of inputs and outputs (the frontier); θ_i is a scalar for each firm, indicating the extent of x_i been used to catch up the optimal combination of inputs, and a value of 1 indicates a point on the frontier hence a technically efficient DMU. I1 is an $n\times 1$ vector of 1, ensuring that sum of all the weights assigned to the benchmarking firms equal to 1, thus the fabricated benchmarks (the optimal combination of inputs and outputs) are similar in scale with the i–th firm (Coelli, *et al*., 2005). Therefore, the DEA model of Eq. (1) seeks to reduce inputs as much as possible, relative to the empirically constructed identical and optimal combination of inputs and outputs for each firm (Maria P., *et al*., 2010).

If the θ_i obtained from the CRS DEA differs from that out of VRS DEA, it indicates the existence of scale inefficiency (Coelli, *et al*., 2005). Thus the θ_i obtained from the CRS DEA (the total efficiency or economic efficiency) is decomposed into two components, one due to the scale inefficiency and one due to pure technical inefficiency (*i.e.* VRS TE).

The nature of returns to scale

The nature of returns to scale can be determined by running an additional procedure with Non–increasing Returns to Scale (NIRS), which can be imposed through substituting I1' λ=1 with I1' $\lambda\leq$1 in Eq. (1). The nature of the scale inefficiencies for a firm can be determined by comparing the NIRS TE with the VRS TE. If they are unequal, then Increasing Returns to Scale (*irs*) exists; if they are equal, then Decreasing Returns to Scale (*drs*) apply; if in a firm where $TE_{CRS} = TE_{VRS}$, *i.e.*., *SE*=1, then the firm is operating under Constant Returns to Scale (*crs*) (Coelli, *et al*., 2005).

Radial and slacks adjustment

Radial and Slacks Adjustment are illustrated in Fig. 1, where efficient firms (the frontier) are assumed using input combinations of *C* and *D*. Meanwhile, *A* and *B* are inefficient firms, with the efficiencies measured as *0A'/0A* and *0B'/0B*, respectively. The distance from an inefficient point, like *A*, to the projected point on the frontier, like *A'*, is called Radial Adjustment (Coelli, *et al*., 2005).

In some cases, Slack Adjustment occurs due to the piece–wise linearity of the non–parametric frontier and finite sample sizes. In Fig. 1, because the section *CS* of the linear frontier is parallel to the vertical axe, the amount of input x_2 can be reduced by *CA'* while producing the same output, thus making *A'* not a most efficient point for firm *A*. The amount of *CA'* is known as Slack Adjustment or Input Excess in the literature (J. Hu, *et al.*, 2006). Therefore, for firm *A*, the total adjustment for input x_2 includes two parts: Radial Adjustment (*A'A*) and Slack Adjustment (*CA'*).

Similarly, in the output–oriented Fig. 2, the efficiency of an inefficient firms *P* can be measured as *0P/0P'*, while output q_2 can be increased by *P'A* as the output slack with the same input, thus making *P'* not most efficient for firm *P*. The total adjustment for output q_2 is divided into two parts: Radial Adjustment (*PP'*) and Slack Adjustment (*P'A*).

Generally, radial and slack adjustment show the inefficient and redundant amounts of inputs respectively, and their summation is the gap between the original and target quantity of each input. In this study, we extend the notion of radial and slack adjustment, i.e., allocate inefficiency (Coelli, *et al.*, 2005), into the models with multiple inputs and outputs, and conduct analyses amongst individual farms.

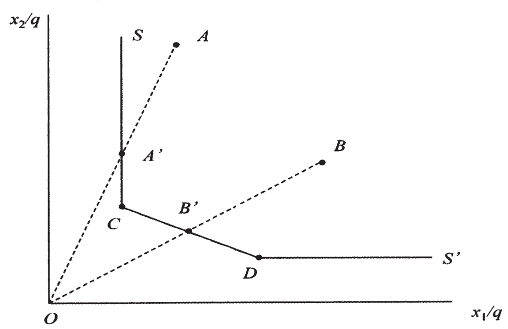

Fig. 1. Efficiency Measurement and Input Slacks. Source: (Coelli, *et al.*, 2005)

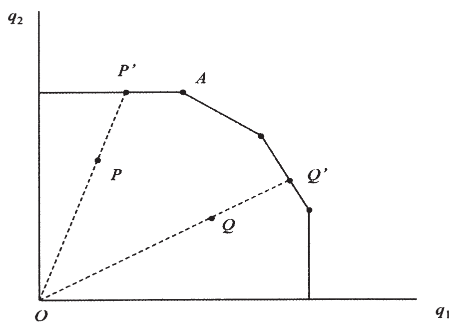

Fig. 2. Efficiency Measurement and Output Slacks. Source: (Coelli, *et al.*, 2005)

DATA AND VARIABLES SPECIFICATION

Data and software

This study is conducted based on data obtained from the farm survey conducted by the authors in August to October, 2010. In this survey, 120 household farms from 48 counties of all the 11 prefectures of Hebei province are interviewed or answered our questionnaire. However, considering the integrity and rationality, responses from 99 farms are used in the study, with a valid ratio of 82.5 percent. Major agricultural products among the sampled farms include staple grain crops of wheat and corn; cash crops of cotton, millet, broomcorn, peanut, soybean, potatoes; and vegetables of cucumber, pepper, lettuce, carrot, etc.

Summary statistics of each variable are listed in Table 1. Through the application of DEAP 2.1, the software kindly provided by Professor Tim Coelli, we solved the input–oriented DEA model with the assumption of VRS, the linear programming problems derived from Eq. (1), as to be shown in the following sections.

Defining the variables

Considering the reality of agricultural production in China, combining with the mechanism of DEA and indications from previous studies, the model specified in this study consists of 2 outputs, 6 inputs and 12 determinants, to measure agricultural production efficiency of the sampled farms (Table 1).

Output variables For most of the farms, agricultural production is not only indispensible source of food material, but also important source of income. Net profit refers to the balance of the gross revenue minus all the costs from annual agricultural production; Ratio of net profit is the percentage of net profits in the total revenue. The gross revenue is defined as sum of all the yields of agricultural products multiplied by the average prices, which are gathered from farms' selling experiences over 12 months until the survey. The costs include the monetary inputs of fertilizer, pesticide, land rent, seeds, machinery rent, irrigation cost, and labor rent.

Input variables (1) Farming time is shown in standardized days. To calculate this variable, farming time of both family members and hired labors are standardized referring to a moderate labor[1], and then divided by 8 hours. (2) Seeds include monetary values of the bought, self–produced and donated seeds. (3) Fertilizer and (4) Pesticides are the amounts of fertilizer and pesticides, respectively. (5) Machine service rent is the expenditure for mechanical operations including ploughing, sowing, harvesting, threshing and transportation. (6) Irrigation costs consist of the expenditure for the rent of irrigating equipments, and other costs occur during irrigation.

Determinants of efficiency The production efficiency of a firm is usually affected by a variety of social and natural determinants, including the natural conditions, change of policies, planting customs, etc. In this

[1] The moderate labors include: 18–50 year old male and 18–45 year old female, who are able to adapt moderate labor intensity; labors out of the age interval stipulated above, but can undertake equivalent labor intensity; the employed labors.

Table 1. Variables and the summary statistics of agricultural production efficiency

Variable		Description of the variable	Unit	Max	Min	Mean	Std. D	C. V.
Output	y_1	Net profit per *mu* [a] (profit)	*yuan/mu*	2424.75	364.53	1117.57	381.03	0.34
	y_2	Ratio of net profit (ratio)	%	84.34	40.48	68.42	8.27	0.12
Input	x_1	Farming time inputted (time)	*day/mu*	17.00	1.00	3.74	2.22	0.59
	x_2	Seeds inputted (seeds)	*yuan/mu*	280.00	25.00	104.77	63.46	0.61
	x_3	Fertilizer inputted (fert)	*kg/mu*	170.00	26.25	65.08	26.97	0.41
	x_4	Pesticides inputted (pesti)	*kg/mu*	2.80	0.00	0.78	0.53	0.68
	x_5	Machine service rent (machr)	*yuan/mu*	150.00	0.00	62.84	37.73	0.60
	x_6	Irrigation costs (irric)	*yuan/mu*	180.00	0.00	57.35	39.39	0.69
Determinant	d_1	Age of farm head (age)	*year*	78.00	31.00	49.54	7.02	0.14
	d_2	Schooling length of farm head (edu)	*year*	15.00	5.00	9.11	2.26	0.25
	d_3	Number of agro–labor (labor)	*person*	5.00	1.00	2.42	0.72	0.30
	d_4	Size of farmland (land)	*mu*	20.00	1.00	6.19	3.94	0.64
	d_5	Ratio of irrigable farmland (irril)	%	100.00	0.00	83.13	27.29	0.33
	d_6	Power of agro–machinery (pw)	*kw*	24.99	0.00	6.02	5.49	0.91
	d_7	Public agricultural subsidies (subs)	*yuan/mu*	140.00	30.00	68.99	24.29	0.35
	d_8	Gender of farm head (gender)	*dummy*	1=male, 0=female; 94 (94.95%) farms with d_8=1				
	d_9	Multiple cropping (mulc)	*dummy*	1=yes, 0=no; 77 (77.78%) farms with d_9=1				
	d_{10}	Growing of cash crops (cashc)	*dummy*	1=yes, 0=no; 30 (30.30%) farms with d_{10}=1				
	d_{11}	Access to credit market (credit)	*dummy*	1=yes, 0=no; 19 (19.19%) farms with d_{11}=1				
	d_{12}	Access to public service (pubs)	*dummy*	1=yes, 0=no; 32 (32.32%) farms with d_{12}=1				

[a] Note: as a main unit of currency and land measurement in China, 6.627 yuan = 1 US$ (middle exchange rate of 2010), 1 *mu*=666.67m^2.
Data source: farm survey in Hebei province

study, we include four categories of variables to identify the effects of these factors: (1) Information of human resources, including age (d_1), gender (d_8), and schooling length (d_2) of the farm heads, and number of agro–labor (d_3) in each farm. (2) Cultivation of land resources, as size of farmland (d_4), ratio of irrigable farmland (d_5), multiple cropping (d_9) and growing of cash crops (d_{10}). (3) Physical and monetary capitals, including power of agro–machinery (d_6), and public agricultural subsidies (d_7). (4) Social and political factors, as access to credit market (d_{11}) and access to public services (d_{12}) by each farm in latest 3 years.

EFFICIENCY ANALYSIS WITH DEA

Total, technical and scale efficiencies

The efficiency summary in Table 2 shows that, within the 99 household farms, 35 farms (Type Ⅰ) are scored 1 in total, technical and scale efficiencies, thus being deemed as in the status of full efficiency and benchmarks for the other inefficient farms. Furthermore, within the rest 64 farms with total efficiency less than 1, 11 farms (Type Ⅱ) bear technical efficiencies equaling to 1. It indicates that in these farms, adjustment of any input will not change the efficiency, thus adjusting their farming scales is the only solution to improve production efficiency. Meanwhile, there are still 53 farms (Type Ⅲ) have technical efficiencies scoring less than 1, indicating that with given farming scales, efficiency can be improved through input reduction.

In terms of the statues of scale efficiency, all the efficient farms are in the status of constant returns to scale, while most of the inefficient farms are being increasing returns, although some of them embrace

Table 2. Efficiency summary by DEA

Type	Number of farms	Means			Number of farms with		
		Total efficiency	Technical efficiency	Scale efficiency	*crs*	*irs*	*drs*
Ⅰ	35	1.000	1.000	1.000	35	0	0
Ⅱ	11	0.891	1.000	0.891	0	10	1
Ⅲ	53	0.619	0.682	0.907	0	46	7
Total	99	0.784	0.830	0.938	35	56	8

Note: *crs* = constant returns to scale; *irs* = increasing returns to scale; *drs* = decreasing returns to scale
Software: DEAP 2.1

decreasing returns to scale (Table 2). Thus the enlargement of scales is necessary for most of the sampled farms.

Slack analysis of the outputs

Slack of an output shows the margin that a firm can improve its output through the adjustment strategies proposed by DEA. The output slacks summarized in Table 3 show that, within the 53 farms of Type Ⅲ, comparing with the absolute output of net profit from agricultural production, the relative output of ratio of net profit can be increased with a larger margin. It indicates that in addition to maintain and increase the price of agro–products, much more endeavors are needed to reduce the costs, cultivate the possible marketing values of agro–products.

Radial and slack analysis of the inputs

Amongst the 6 inputs, there is no significant difference in the ratio of radical adjustments (Table 4). By contrast, ratios of slacks differ among different inputs. As implicated by Martine, *et al*. (2003), the slacks indicate inputs in excess supply, i.e., a smaller percentage of slack movement shows the input is used more efficiently. Within Type Ⅲ, farming time and agro–machinery rent are used most efficiently, showing the general trend of labor transferring to non–agricultural sectors and the large space of extending agro–machineries. Irrigation cost is measures as with the largest slacks, indicating the unbalanced development of irrigating facilities.

EFFECTS OF THE DETERMINANTS ON TECHNICAL EFFICIENCY

Ordinal logistic regression models

In cases of the dependent variables are put in ordinal categorical responses, the ordinal logistic regression model can be applied to measure effects of the determinants (A. Uzmay, *et al*., 2009; Maria P., *et al*., 2010). Considering $k+1$ ordered categories, the basic models are defined as:

$$\mathrm{P}(Y \leq i) = p_1+p_2+\ldots+p_i \qquad (i=1, 2, \ldots, k) \quad (2)$$

$$odds\ (Y \leq i) = \frac{P(Y \leq i)}{1-P(Y \leq i)} = \frac{p_1+p_2+\cdots+p_i}{p_{i+1}+p_{i+2}+\cdots+p_{k+1}} \qquad (i=1, 2, \ldots, k) \quad (3)$$

$$logit\ (Y \leq i) = ln\left[\frac{P(Y \leq i)}{1-P(Y \leq i)}\right] = \alpha_i+\beta_{i1}X_1+\beta_{i2}X_2+\cdots+\beta_{im}X_m \qquad (i=1, 2, \ldots, k) \quad (4)$$

where α_i and β_{ij} represents the threshold (j=1, 2, …, m) parameters; X_{ij} are sets of factors or predictors. Eq. (4) is a general ordinal logistic model for m predictors with $k+1$ ordered response variables. This model depends on cumulative probabilities of the dependent variable categories, and contains a large numbers of parameters as there are k equations and one set of logistic coefficient β_{ij} for each category (Ralf B., *et al*., 1997; Adeleke K. A., *et al*., 2010).

However, in case of the responses are fabricated from continuous variables, like the farm categories grouped respect to the technical efficiencies by DEA model in this study, a more parsimonious model is applicable. We can assume a parallelism between regression functions of different categories and logit scales (A. Uzmay, *et al*., 2009). Namely, the logistic coefficients do not depend on i, but have one common parameter β_j for each covariate. It follows that cumulative odds model is given by:

$$odds\ (Y \leq 1) = exp(\alpha_i)\ exp(\beta_1X_1+\beta_2X_2+\ldots+\beta_mX_m), \qquad (i=1, 2, \ldots, k) \quad (5)$$

which means that the k odds for each cut–off category i

Table3. Slack analysis of outputs in farms of Type Ⅲ

	Net profit of agricultural production (*yuan/mu*)			Ratio of net profit (%)		
	Origin1	Target1	Slack1	Origin2	Target2	Slack2
Slack movement	1118.386	1181.860	63.501	65.821	77.374	11.553
Percent of slack (%)	100.00	105.678	5.678	100.00	117.551	17.551

Software: DEAP 2.1

Table 4. Radial and slack analysis in farms of Type Ⅲ

		Time (*day/mu*)	Seeds (*yuan/mu*)	Fert (*kg/mu*)	Pesti (*kg/mu*)	Machr (*yuan/mu*)	Irric (*yuan/mu*)
Mean movements	Radial	1.192	48.546	25.339	0.272	25.337	22.990
	Slack	0.182	18.910	7.796	0.136	5.790	20.290
	Total	1.374	67.457	33.135	0.408	31.127	43.280
Percent of movements (%)	Radial	33.146	37.141	33.111	30.660	33.817	33.514
	Slack	5.051	14.468	10.187	15.358	7.727	29.578
	Total	38.197	51.609	43.298	46.018	41.544	63.092

Software: DEAP 2.1

differ only with regard to the intercepts α_i. Therefore, the effect of a covariate can be quantified by one regression coefficient, and the calculation for one common *odds ratio* is possible, thus the presentation of results is shorter and simplified (Ralf B., *et al*., 1997).

Model specification

In order to conduct an ordinal logistic regression, the sampled 99 household farms are divided into seven groups, in terms of their technical scores provided by DEA. The summary statistics for each group are given in Table 5.

Like applying the other regression models, correlation test between the predictors is necessary, to detect the possible interactions. As the Pearson correlation matrix of the determinant variables shown in Table 6, statistically significant correlations occur in 10 pairs of predictors. The significant correlation indicates underlying strong interaction, which affects the accuracy to model the relationship of the predictors and the responses. Therefore, based on the significantly correlated determinant variables, 10 covariates are constructed and put into the ordinal regression model, thus number of the predictors increased to 22 in total.

Maximum likelihood estimation of a proportional odds model is carried out through application of the Ordinal Logistic Regression procedure in SPSS 13.0. The stepwise backward approach is applied to remove the statistically insignificant variables (p–value$\geq$0.1), from the initial model with all the 22 determinants as independent variables. The final model includes 5 predictors, all of which embrace p–value less than 0.1. Assumption of parallelism is confirmed where we accept the null hypothesis of equal location parameters (slope coefficients). The Chi–square value of 12.377 at the freedom degree of 25 is not statistically significant, hence the assumption of parallelism is satisfied (Adeleke K. A., *et al*., 2010). Meanwhile, the model fitting information (p–value=0.000) shows that the null hypothesis should be rejected, and at least one of the regression coefficients in the model is not equal to zero at the alpha level of 0.01 (Table 7). Therefore, the model fits well relationships of the independents and dependents.

Results and discussion

In Table 7, the *Estimate*s are the ordered log–odds regression coefficients, of which the standard interpretation is that for a one unit increase in the predictor,

Table 5. Case processing summary statistics

Group	Technical Score*	N	% of N	Max	Min	Mean	Std.D	C. V.
1	0.40–0.50	7	7.10	0.497	0.430	0.458	0.026	0.058
2	0.50–0.60	13	13.10	0.594	0.508	0.559	0.026	0.046
3	0.60–0.70	9	9.10	0.696	0.601	0.646	0.026	0.041
4	0.70–0.80	6	6.10	0.778	0.723	0.754	0.021	0.028
5	0.80–0.90	15	15.20	0.892	0.807	0.853	0.024	0.028
6	0.90–1.00	2	2.00	0.939	0.935	0.937	0.003	0.003
7	1.00	47	47.50	1.000	1.000	1.000	0.000	0.000
Total		99	100.00	1.000	0.430	0.833	0.194	0.232

Note: *the upper limit is not included in each group
Software: SPSS 13.0

Table 6. Pearson correlation matrix of the determinant variables

	Age	Edu	Labor	Land	Irril	Pw	Subs	Gender	Mulc	Cashc	Credit	Pubs
Age	1	–0.304**	0.174	–0.010	–0.176	–0.010	–0.073	–0.174	–0.001	–0.051	–0.03	0.139
Edu		1	–0.200*	–0.049	0.147	–0.027	0.010	0.011	0.07	0.143	0.01	–0.159
Labor			1	0.041	0.177	–0.175	0.152	–0.122	0.148	–0.146	–0.074	0.165
Land				1	0.106	0.387**	0.051	0.088	0.028	0.324**	0.043	0.02
Irril					1	–0.141	0.315**	–0.143	0.239*	0.107	–0.095	0.156
Pw						1	0.062	0.000	0.096	0.297**	0.226*	–0.169
Subs							1	–0.188	0.329**	–0.033	0.126	0.032
Gender								1	–0.123	0.052	0.112	–0.038
Mulc									1	–0.176	–0.048	0.006
Cashc										1	0.069	–0.08
Credit											1	0.212*
Pubs												1

Note: **and *represent statistical significance in the level of 5% and 10% respectively
Software: SPSS 13.0

extends that the response variable levels are expected to change in the ordered log–odds, while the other variables are held constant (Bruin J., 2006). For instance, the estimate of age means that, if a farm were to increase the head's age by one year, his ordered log–odds of being in a higher category of technical efficiency would increase by 0.136 while the other variables held constant. The Wald statistic is the square of the ratio of the coefficient to its standard error. The odds ratios of the predictors are calculated by exponentiating the estimates (*i.e.*, odds ratio=e^{β}), thus they indicate probabilities of the response variable level changing to a higher score, due to one unit increase of the predictor. Meanwhile, the lower and upper bounds of odds ratio for each predictor are listed as Confidence Interval (CI), under the confident level of 0.95.

According to the coefficients, *age*, *gender*, and *crtps* increase, while *labor* and *pubs* reduce the odds of a farm be measured to a more efficient group. In other words, the sampled farms with aged and male head are more probably to be efficient, while the number of agro–labor is negative to agricultural production efficiency. Moreover, the integration of public services with farms' access to the credit market is positive to agricultural production efficiency. These findings are testified by comparison of farms in different groups (Table 8).

(1) Effects of age and gender of the farm heads.

The positive relationship of technical efficiency and farm heads' age is demonstrated in Table 8, together with the larger average efficiency score of farms headed by males. The positive effects of these two predictors indicate that in the sampled areas, farming are mainly relying on personal experiences, using traditional production modes or simply imitating the others (L. Wang, *et al*., 2003). This result is in line with Z. Chen, *et al*. (2009) and S. Tan, *et al*. (2010), concluding that farmers with more farming experiences (measured by the household heads' age) have greater farm technical efficiency, consistent with a large amount of information. The professional human resources being able to cultivate and apply agricultural technology are highly needed for efficient farming activities.

(2) Effects of agro–labor numbers

This negative effect from numbers of agro–labors indicates the existence of surplus labor in Chinese agriculture, being consistent with Z. Chen, *et al*. (2009), H. Dong, *et al*. (2010) and D. Li, *et al*. (2011). Therefore, the continuing transfer of surplus labor from agriculture to the other sectors is still of great importance in China.

(3) Effects of access to credit and public services

In this survey, within the latest three years, the farms got public services mainly from the local government and their branches, including the extension of new varieties of agricultural products, aids of setting up cash crop facilities, unified purchase of farming goods, etc. However, as average scale of farmland is less than 0.5 hectare per farm, and farmers are poor with expert knowledge of modern agricultural production. Thus the new farming modes and varieties are difficult to be efficiently extended. On the contrary, they may increase the finan-

Table 7. Parameter estimates of ordinal logistic regression

	Estimate	Std. error	Wald	*df*	*sig.*	odds ratio	95% confidence interval	
							Lower bound	Upper bound
Age	0.136 ***	0.035	15.540	1	0.000	1.146	1.071	1.226
Labor	−1.059***	0.300	12.494	1	0.000	0.347	0.193	0.624
Gender	1.712*	0.908	3.557	1	0.059	5.539	0.935	32.805
Pubs	−1.387 ***	0.486	8.143	1	0.004	0.250	0.096	0.648
Crtps [a]	2.210***	0.811	7.429	1	0.006	9.112	1.860	44.635

Test of parallel lines [b]: LR Chi–square (25)=12.377; Sig.=0.983
Model fitting information: LR Chi–square (5)=34.385; Sig.=0.000

Note: ***and *represent statistical significance in the level of 1% and 10% respectively
[a] *crtps* is a covariate constructed based on *credit* and *pubs*.
[b] The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.
Software: SPSS 13.0

Table 8. Descriptive comparison of farms in different groups

Determinant	Age of farm head						Gender of farm head	
Group	<40	[40, 45)	[45, 50)	[50, 55)	[55,60)	≥60	0	1
Number of farms	4	12	39	23	13	8	5	94
Mean of tech	0.523	0.790	0.855	0.866	0.772	0.954	0.686	0.841

Determinant	Number of agro–labor					Pubs		crtps	
Group	1	2	3	4	5	0	1	0	1
Number of farms	2	63	25	8	1	67	32	89	10
Mean of tech	1.000	0.853	0.828	0.693	0.490	0.854	0.790	0.825	0.905

cial burden of farmers or break their accustomed farming modes and undermine the production efficiency. Hence a negative relationship is found in the aforementioned analysis.

However, when analyzing with *crtps*, the odds of increasing efficiency with farms who have incorporated the effects of farms' accessed to both the credit market and public services, is doubled three times than the farms that have not (Table 7). Comparing from the technical scores, the former group (*crtps*=1) scored higher than the latter (*crtps*=0, Table 8). S. Tan, *et al*. (2010) demonstrated the importance of credit availability in improving technical efficiency of rice farming in China. It shows that the integration of credit supply and public services are indispensable to improve agricultural production efficiency for the farms.

Discussion on the other determinants

Although modeled as insignificant in the ordinal logistic regression model, the other determinants are still affecting the production efficiency and need to be examined for referential implications.

(1) In the first category of human resources, schooling length of the farm heads is the only determinant being excluded as significant to production efficiency. This result verifies the aforementioned reality that agricultural production is carrying out mainly relying on farmers' private experiences, rather than the adoption of advanced technologies. Hence for most farmers, knowledge learnt at school did not make much difference in improving their agricultural production efficiency.

(2) The second category do not pass the significant test, showing that sizes of farmland sampled are not large enough for adopting more efficient farming modes, including the large machineries and modern managerial strategies, i.e., cannot generate scale economy. For farms with irrigable farmland less than 100 percent, the average technical efficiency scored 0.879, larger than that of the farms with all the farmland irrigable. The reason behind is that in most cases, all farmland irrigable means good natural condition and thus larger population and smaller plots of farmland. In this survey, average farmland sized 6.56 *mu* with farms having part of irrigable land, while 5.97 *mu* with farms embracing totally irrigable farmland. Moreover, the insignificant contribution of multiple cropping and growing of cash crops may due to extensive cultivation of resources, especially water, fertilizer, etc. For example, in this survey, the multiple cropping farms use 69.3 *kg* fertilizer for each crop per *mu*, which is 19 *kg* more than single cropping farms; the farms growing cash crops spend 32.92 percent in irrigating and use 32.03 percent of pesticides, more than those growing only grain crops.

(3) For the physical and monetary capitals, as to the insignificant effects of agro–machinery, its connecting with low efficiency of mechanical operations out of the small sized farmlands as mentioned above. For public agricultural subsidies, the insignificancy may result from the relative low ratio in farms' total cost (as 13.91 percent in this survey). The average technical efficiency score for farms subsided more than 100 yuan per *mu* is 0.933, while 0.822 amongst farms subsided no more than 100 yuan per mu. This result shows the necessity of improve the amounts of agricultural subsidies. X. Yang, *et al*. (2010) concluded similarly that most of the farms in their survey claimed more agricultural subsidies and the funds should be granted to the real grain–growing farms, rather than distributing out simply according to sizes of farmland.

(4) In the fourth category of social and political factors, no significance captured from access to credit market by the ordinal logistic regression model. However, in the farms accessed to the credit market within latest three year, the average technical efficiency scored 0.873, which is larger than the value of 0.824 with farms who did not access. The causes of relatively poor efficiency of credit market include the lack of effective projects and managerial strategies supported public services. Meanwhile, some farms loaned for non–agricultural affairs, while many farms borrowing from relatives as surveyed by Calum G, *et al*. (2010).

CONCLUSIONS AND RECOMMENDATIONS

Main conclusions

This study measures the agricultural production efficiency in Hebei Province, China, through the adoption of DEA and ordinal logistic regression models. According to the efficiency scores of DEA, the 99 sampled household farms are divided into 3 types. In Type I, the 35 farms are fully efficient and in the status of constant returns to scale, thus can be esteemed as benchmarks for the other farms. In the 11 farms of Type Ⅱ, due to the technical scores fixed to 1, adjustment of any input will not change the output efficiency, thus production efficiency can only be improved through expanding the managerial scales in 10 farms, while compressing in one farm. Meanwhile, in the 53 farms of Type Ⅲ, production efficiency can be improved through either reducing some of the inputs or adjusting the managerial scales with expansion in 46 and compression in 7 farms.

The output slacks show that comparing with net profit, ratio of net profit can be increased with a larger margin. Percentages of input slacks show that farming time and agro–machinery rent are used with highest efficiency, while irrigation cost is supplied with largest excess, following by seeds, pesticides and fertilizer.

In the second stage, significant coefficients of the ordinal logistic regression model show that farms with aged and male head are more probably to be efficient, the increasing of agro–labor has negative effects, and the public services do not improve the agricultural production efficiency, unless it is conducted with farms' access to credit market.

Policy recommendations

(1) On the basic production factors. As more than half of the sampled farms are in the status of increasing returns to scale, and size of farmland sampled is demonstrated as not large enough for generating scale econ-

omy. Being the major measurement of farming scale, farmland size should be increased through accelerating the circulation and concentration of land–use right among farms. In China, as land is performing as self insurance of subsistence, farmland should be concentrated on farmers' own will, through favorite subsidies.

Considering the negative effects of aro–labor numbers, surplus labors need to be further transferred from agriculture to the other sectors. The major obligations for the government include promoting the implementation of Sunlight Project, perfecting the construction of employment information networks, and protecting the legal rights of migrant workers[2]. Meanwhile, as the farmers are mainly relying on personal experiences and traditional modes or imitating the others, advanced agricultural techniques and managerial strategies should be introduced into the vocational training of Sunlight Project, hence improve their farming efficiency.

(2) On the other production factors. To tackle with the large slacks in pesticides and fertilizer, instruction on proper use of agricultural chemicals should be strengthened. Priorities should be placed on the field tests thus decide the appropriate amounts and balanced ingredients. The manufacturers, research institutes, etc, can play critical roles in terms of technical supporting, through innovating and extending their services to farmers (H. Han, *et al*., 2009). As proposed by R. Hu, *et al*. (2009), separating commercial activities from the agricultural sci–tech extension agencies and corresponding subsidies are important as well. Hence these institutions can benefit from the applicability of their research achievements in improving production efficiency of farms.

Being another important factor, high quality seeds should be guaranteed. In spite of the conducting public funds that subsiding the using of quality seeds by the farms, they are generally being distributed simply based on the areas of farmland in practice, as it is difficult to make sure that the subsided farms are used the quality seed (X. Yang, *et al*., 2010). Therefore, the government should subsidize R&Ds on quality seeds directly, and strengthen the supervision of seeds markets, thus guarantee the quality and reduce the costs simultaneously.

(3) On the construction of public agro–facilities. Since irrigation costs embraced the largest slacks, the quality of irrigation facilities is of great importance to improve production efficiency. The governments should invest more fiscal funds and channel more social capitals to the construction of irrigating and water conservancy facilities. Priorities should be placed on the efficient usage of water and cutting down the irrigating costs.

(4) On the public services. Closer integration of the aforementioned public services and efficient credit market needs to be accelerated. The rural financial institution should be encouraged in innovating institutions on granting credit to farmers, such as granting loans with mortgage on land–use right, taking external permanent staffs as guarantors, etc. Moreover, public services concerning credit access can be entrusted to the farmers' cooperatives, which are developing quickly in latest years, thus improve the credibility of farmers and increase the funding efficiency.

Open research topics

This study conducted household farm survey in Hebei Province, China, and measured the overall agricultural production efficiency of each farm in 2010. In the future researches, if the survey can be expanded to a larger region or even the whole country, taking more specific items to included crop–based inputs. Thus production efficiency of comparison of different regions and crops can be realized. In addition, special study can be conducted with focuses on the enlargement of farming scales, especially farmlands, proper use of agricultural chemicals, construction of public agricultural facilities, etc. Moreover, years of continuous study will provide a valuable database for the exploring laws of agricultural production efficiency, hence be referential for further policy recommendations.

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[2] Sunlight Project is a series of vocational training of rural labor force organized by Chinese government since 2004. Its purpose is to improve the quality of the rural labor force and professional skills, thus promoting their stable employment and income growth when migrant to the urban areas or rural non–agricultural sectors.

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