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Farm Technology and Technical Efficiency: Evidence from Four Regions in China

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Abstract

In this paper we fit stochastic frontier production functions to data for Chinese farms grouped into each of four regions—North, Northeast, East, and Southwest—over 1995-1999. These frontier production functions are shown to have statistically different structures, and the marginal product information shows overuse of chemical inputs in the East and capital services in the North. Labor also has a low marginal product. Next, we use the data and the production parameters to create technical efficiency scores for each of the farms and then standardize them. Standardized technical efficiency is shown to have the same structure across regions and to be related to the age of the farmer, land fragmentation, and the village migration rate, controlling for year dummies and village or regional fixed effects.

JEL Classification: C23, D24, N55, O13

Keywords: Household farm; Labor migration; Land fragmentation; Stochastic production frontier; Technical efficiency

1. Introduction

For more than two decades, China has had an annual growth rate of real income per capita of approximately 10 percent, causing a rapidly growing demand for protein-rich diet, particularly of livestock products which have high income elasticities and are very grain intensive to produce. Hence, the increasing demand for grain due to income and population growth has evoked debates on how well China can feed itself in the future (Brown 1995). The extant literature has seen a great many discussions on whether viable options remain for improving agricultural production in China. The role of technical and allocative efficiency was investigated in Mao and Koo (1997), Wang, Cramer, and Wailes (1996) and others (see, also, a discussion in Abdulai and Huffman 2000). Reducing land fragmentation was examined in Wan and Cheng (2001) and Wu, Liu and Davis (2005). Zhang and Fan (2004) indicated that public inputs, in addition to conventional inputs, have contributed to growth in agricultural production. Evenson and Gollin (2003) showed that considerable yield potential remained in Green Revolution crop varieties and elite lines that China might exploit, as well.

Nonetheless, several issues still remain unresolved. First, with the rural labor markets that have emerged in rural China, the effect of labor migration on agricultural production efficiency has not yet been well-studied. It has been argued that labor migration has left a majority of female and elderly laborers in the farm fields, and is, thus, detrimental to agricultural production. Meanwhile, labor migration could improve allocative efficiency through better information transmission, and technical efficiency through industrial inputs purchased with remittances. Labor migration also helps in land consolidation. Hence, it is of great interest to determine the overall effect of labor migration, given the importance of related policy implications. Second, no consistent conclusion has been drawn on the role of land fragmentation. Wan and Cheng (2001) found it detrimental but Wu, Liu and Davis (2005) suggested no statistically significant effects of land fragmentation. Existing studies are compromised by inadequate measurement of land fragmentation, e.g., many have used the number of plots, which indeed reflects land fragmentation to a certain extent, but cannot capture the variation in average plot area. While land fragmentation has been examined in the aforementioned studies, none of them have investigated the relationship between land fragmentation and technical efficiency. Last, although previous studies have examined the roles of inputs in Chinese agricultural production using different methodologies (see, e.g., Chen and Huffman 2006, Fan and Zhang 2002, Tian and Wan 2000, Wu, Liu and Davis 2005, and Zhang and Fan 2001), many of them used aggregate datasets or data of the mid-1990s. It is important for the research community to see new estimates of production and efficiency functions for Chinese farms obtained from updated household level dataset.

Farm production decisions of modern Chinese farmers fit the agricultural household model (Huffman 2001, Strauss 1986). In China's agriculture, land and family labor continue to be the dominating inputs. But prices for these are not readily available, making a cost function approach infeasible. This study chooses an alternative route of estimating stochastic frontier production functions. A notable feature of China's agriculture is that China spans a large geographical area; thus, the climate, soil conditions, and even institutions vary across regions. Households in different regions may apply different technologies, or their frontiers may shift due to variations in land quality and weather conditions. Ignoring these factors could lead to biased estimates of the frontier production function.

The objective of this paper is to provide new evidence on the parameters of the farm level stochastic frontier production function in China and to examine technology scores obtained from these functions and the sample information. The study uses a panel of 591 Chinese farms, 1995-1999 and applies a two-stage methodology. First, the stochastic frontier production function is fitted to each of four regions—the North, Northeast, East, and Southwest, which are shown to have statistically different structures. Efficiency scores are then computed for each farm and standardized. These standardized efficiency scores are pooled across the four regions and then regressed on measures of land fragmentation, labor migration and other household and village characteristics. The justification for this methodology is that the agricultural production function in each region is distinctive from that of the others, but the pathways in which demographic and institutional variables influence technical efficiency are similar across all farm households. To our knowledge, our data set is one of the newest household-level dataset on China's agriculture, providing random sampling and broad geographic coverage.

The rest of the paper is organized as follows. Section 2 reviews the literature on agricultural production in China. The econometric methodology is outlined in Section 3 and the data set and construction of variables are described in Section 4. Section 5 presents the results and Section 6 concludes the paper.

2. Agriculture in China

Given the task of feeding a growing population of about 1.3 billion, the agricultural sector is of great importance to China. China's agriculture is well-known for the reform of the later 1970s and subsequent successes (see, e.g., discussions in Pomfret 2000 and Rozelle et al. 2000). Many have tried to determine what underlies these successes. The changing role of inputs, the rapidly updating technology, and the effects of deepening human capital and evolving institutions are of particular interest. For the years immediately following the agrarian reform, Lin (1987) attributed a large share of productivity growth to institutional change that eliminated much of the "shirking" of laborers under collective farming. De Brauw, Huang, and Rozelle (2001) argued that market liberalization was another contributing factor. The second decade after the reform brought more changes. The role of the increased usage of modern inputs such as modern crop varieties, fertilizers, and pesticides on agricultural production may have been underestimated (Xu 1999). Widawsky et al. (1998) concluded that pesticides were overused in eastern China where host-plant resistance had developed. Excessive labor may still exist in China's agriculture, as well (Wan and Cheng 2001 and Fan, Zhang and Robinson 2003). Wan and Cheng (2001) found that labor productivity for some crops could be close to zero. Fan, Zhang and Robinson (2003) suggested that labor productivity in the agricultural sector remained low as a result of continuing large surpluses of rural labor. Meanwhile, they found that the returns to capital investment in agricultural production were much higher than those in urban sectors, suggesting underinvestment in the agricultural sector.

Besides technology parameters, rural institutions are one of the focal points of the studies on China's agriculture. China does not have private land ownership, so a local village council allocates land based on a farm households need and sets rental rates. Hence, this village council is an institution with possible productivity effects. Cheng (1998) concluded that a household having a member on the local "village council" had positive efficiency effects through better access to collectively-owned farm equipment and state-subsidized farm inputs. In addition, under the household responsibility system, farm size remains small and fragmented in China, but no consensus exists on whether the small farm size and land fragmentation are a drag on productivity or efficiency (see, e.g., Wan and Cheng 2001, Wang, Cramer, and Wailes 1996, and Wu, Liu and Davis 2005). Generally, it is believed that land fragmentation has caused a waste of land in demarcation and access routes, as well as a waste of industrial inputs, such as fertilizers and pesticides, during transportation from one plot to another. The role of human capital has inspired many discussions, as well. For agriculture in general, Huffman (1977), and for China in particular, Cheng (1998), Wang, Cramer, and Wailes (1996) and Yang (1997) have shown that farmers' schooling has positive effects on technical and allocative efficiency.

3. Model Specification

Farm technical efficiency is the ability of a farmer to maximize output with given quantities of inputs and a certain technology (output-oriented) or the ability to minimize input uses with a given objective of output (input-oriented). Output-oriented technical efficiency is more commonly used in empirical applications and is defined as

$$TE_o(y,x) = [\max\{\phi : \phi y \in \{y : x \text{ can produce } y\}\}]^{-1}.$$

In this paper, we derived measures of output-oriented farm level technical efficiency indexes using the SFA. Although there is a continuing debate whether deterministic methodologies such as data envelopment analysis, or stochastic methodologies such as the SFA should be used (see, e.g., a discussion of deterministic and stochastic efficiency models in Bravo-Ureta and Rieger

1990), we believe that measurement errors and weather-related disturbances in China make SFA preferable in this particular study. Thiam, Bravo-Ureta and Rivas (2001) provided a meta-analysis, reviewing empirical estimates of technical efficiency in developing country agriculture, and found that stochastic versus deterministic frontiers do not seem to significantly affect estimates of technical efficiency across studies.

The SFA model dates back to Aigner, Lovell, and Schmidt (1977) and to Meeusen and van den Broeck (1977). Empirical applications include those in Abdulai and Huffman (2002) on rice farmers in Northern Ghana, Bravo-Ureta and Evenson (1994) on peasant farmers in eastern Paraguay, Chen and Huffman (2006) using a county-level dataset of China, and Xu and Jeffrey (1998) on a cross-section of Chinese farm households, and many others.

This paper adopts a model proposed in Battese and Coelli (1992) that can be expressed as:

$$Y_{itr} = f(x_{itr},\beta_r) + (V_{itr} - U_{itr}),\ i=1,\ldots,N,\ t=1,\ldots,T;\ r=1,..,R, \tag{1}$$

where for the i-th farm at time t in the r-th region: Y_{itr} is output (or its transformation); x_{itr} is a $k\times 1$ vector of the inputs (or their transformation); β_r is the coefficient vector of x_{itr}. V_{itr} are random disturbance terms that are assumed to be *iid* $N(0,\sigma_{vr}^2)$. They are incorporated into the model to reflect the random disturbance that is independent of U_{itr}, which represent technical inefficiency in production and are defined as

$$U_{itr}= U_{ir} \exp(-\eta_r(t-T)) \tag{2}$$

where U_{ir}s are non-negative random disturbances that are assumed to be independently distributed and truncated at zero of the $N(\mu_r,\sigma_{ur}^2)$ distribution. η_r is an unknown parameter to be estimated. The relationship between U_{itr} and the output-oriented technical efficiency TE_o is $TE^{irt}_o=\exp(-U_{itr})$. The non-negative firm effects U_{itr} decrease (increase) if η_r is greater (less) than zero. The model degenerates into a specification with time-invariant firm effects if η_r equals zero.

We follow earlier studies, e.g., Battese and Coelli (1995) and Guilkey, Lovell and Sickles (1983), that have chosen as the functional form of the production frontier a translog algebraic function that is flexible and a second-order approximation to any true functional form. It places far fewer restrictions before estimation than the more traditional Leontief, Cobb-Douglas, or CES technologies (Chambers 1998, p. 27-28, 179-181).

Consider the following translog stochastic frontier production function for a particular region (i.e., ignoring subscript r):

$$\ln(Y_{it}) = \beta_0 + \sum_{l=96}^{99} \beta_l d_l + \sum_v \beta_v d_v + \sum_{j=1}^{4} \beta_j \ln(x_{ijt}) + \sum_{j \le k}^{4} \sum_{k=1}^{4} \beta_{jk} \ln(x_{ijt}) \ln(x_{ikt}) + V_{it} - U_{it}, \quad (3)$$

where j, k index inputs used. The d_ls are the year dummy variables for 1996-1999, with 1995 as the reference year.

The second stage of our analysis is to explain farm level technical efficiency scores using a set of regressors. Problems arise because the efficiency scores are constrained between zero and one and because we have four regions, which may have different means and standard deviations. To address these two issues, we first follow Abudulai and Huffman (2000) in transforming technical efficiency scores take values from minus to plus infinity. The procedure is summarized as: at time t, for a household i in region r, its predicted (un-transformed) efficiency index is $\hat{TE}_{\ell}^{it}$, and the transformation is:

$$e_r^{it} = \ln\left(\hat{TE}_r^{it} / (1 - \hat{TE}_r^{it})\right), r = 1, 2, \ldots, 4. \quad (4)$$

The second step involves standardizing the efficiency scores using a procedure suggested by Wayne Fuller (see footnote 11 of Huffman and Keng 2006). The procedure is:

$$e^{it} = e_r^{it} / std_r, r = 1, 2, \ldots, 4, \quad (5)$$

where std_{ℓ} is the standard deviation of e_{ℓ}^{it} for the r-th region, i.e., the North, Northeast, East, and Southwest. Finally, we regress e^{it} on a set of explanatory variables.

4. The Data

The data used in this study are from a unique panel of Chinese farms that is part of a large comprehensive survey conducted by the Research Center for Rural Economy (RCRE) at the Ministry of Agriculture (MOA). Started in 1986 in 29 provinces of China, it contains more than

20,000 households. A nice attribute of this panel is that attrition has been small. However, the survey was temporarily discontinued in 1992 and in 1994 for financial reasons. The overall survey was conducted by provincial offices under the MOA. The data set for our study contains 591 farm households living in 29 randomly selected villages within 9 provinces in China, 1995 to 1999. The nine provinces are Hebei and Shanxi of North China; Heilongjiang and Liaoning of the Northeast; Anhui, Jiangsu, and Shandong of the East; and Sichuan and Yunnan of the Southwest. A detailed list of the villages is available from the authors upon request. The RCRE claimed that 80 percent of the households remained in the survey for the period 1986-1997. More information is available from the RCRE website.[1]

The farm panel used in this study is unbalanced, because not all farm households are reported to be in agricultural production every year. In addition, we had to delete a small number of observations because of data recording mistakes and missing information. These were, however, a negligible fraction of the whole data set. Using the general retail price index, all monetary variables, such as prices, incomes, and expenditures, were converted into real terms with 1986 as the base year. Sample mean values for the four regions are reported in Table 1. We did not present the summary statistics by year because there is no obvious trend.

We follow the existing literature, e.g., Liu and Zhuang (2000), in constructing the output and input variables. The output is measured as the total value of agricultural products, calculated as the sum of the sale of agricultural products and the value of the remaining crops at the end of the year. Although the real output in kilograms is also available in the data, we choose to use the value, because the majority of rural Chinese households produce more than one variety of crop, e.g., rice, wheat, corn, and soybeans, and the aggregation may bias the estimation due to different compositions across regions/households. Inputs used in this study include land area under cropping (measured in Mu), labor employed in cropping (measured in man-days), total current expenditure (measured in RMB Yuan) on fertilizer and pesticides, and capital input used in

[1] http://www.rcre.org.cn/RCRE/GDGC/gdgcposition.htm.

cropping (measured in RMB Yuan).[2] Capital input is calculated as the sum of the depreciation of fixed assets, i.e., agricultural machinery and tools, and the current expenditure on seeds, etc. The average value of agricultural production varies significantly across regions. The Northeast has the highest value, while the Southwest has the lowest. A similar pattern exists for land input, but the ranking of average labor input is very different. Basically, farms in the Northeast are larger and farms in the Southwest are more labor intensive. Farms in the East use the highest amount of fertilizer and are the most capital-intensive. Such contrasts justify estimation of a separate stochastic frontier production function for each region.

Village migrant ratio is calculated as the ratio of the number of migrants in the village to the total labor in the village. It is obtained from the associated village survey as a part of the RCRE dataset. Therefore, the variable could be treated as exogenous to the migration decisions of the households in the sample. Village migrant ratios are different across regions, with Southwestern villages the highest and Northeastern villages the lowest. This is consistent with the common perception of Chinese migrant networks. The household head's age varies across regions, as well. The Southwest has the highest percentage of household heads that are less than 31 years old, and the majority of Eastern household heads are between 31 and 60. Eastern farms are more likely to be mechanized and farms in the North follow. It is a bit surprising that farmers in the Northeast are least likely to use machinery. A possible scenario is that although some of the Northeastern farms are large and use heavy machinery, most of them do not.

Measurement of land fragmentation has long puzzled researchers working on China's agriculture. Previous studies, e.g., Fleshier and Liu (1992) and Wan and Cheng (2001) used number of plots as a proxy of land fragmentation. Wu, Liu and Davis (2005) was one of the first studies to use the Simpson Index (SI) and average plot size to capture two dimensions of land fragmentation. They found no effect of land fragmentation on the average production function. However, land fragmentation may affect production efficiency instead of the frontier or average production function, especially given the potential collinearity between number of plots or plot

[2] 1 Mu=1/15 Hectare; 1 RMB Yuan=$0.12, approximately.

size and total cultivated area. In this study, we explicitly model land fragmentation as a factor determining efficiency rather than determining production frontier. Land fragmentation is measured by number of plots and SI. The number of plots in this sample has a very skewed distribution, ranging from one to forty-five, with an average of about six plots per household. Hence, we estimate a spline function of number of plots by including three dummy variables indicating whether the number of plots falls into the third, second, or first quartile. The reference category is those households where their number of plots falls into the lowest quartile. The SI measures the extent of land fragmentation as follows:

$$SI = 1 - \sum_{i=1}^{n} a_i^{\,2} \Bigg/ \left(\sum_{i=1}^{n} a_i \right)^2 , \qquad (6)$$

where a_i is the area of an individual plot. SI falls between zero and one. It equals zero for a land holding containing only one field, and one for an extremely fragmented holding comprised of an infinite number of plots. Therefore, if SI increases, the degree of land fragmentation is higher.

5. Results

In this section we summarize the results from fitting four stochastic frontier translog production functions, from our empirical technical efficiency scores, and from fitting an econometric efficiency equation. The software used to estimate the stochastic frontier models is FRONTIER 4.1 developed by Coelli (1996), which is a maximum likelihood estimator.

The estimates parameters of the stochastic frontier productions functions are reported in table 2. They are fitted with village fixed effects which will reduce biases associated with left-out variables such as soil quality, pests, and weather which seem likely to be correlated with village dummies. Most of the estimated parameters differ across regions, and we reject the null hypothesis that they are equal at the 5 percent level. Our estimates of γ range from 0.658 for the North to 0.912 for the Southwest. Except for the North, the estimates of γ are greater than 0.80, implying that the one-sided random inefficiency component strongly dominates measurement error and other random disturbances. The estimates of η_r are negative for all four regions.

Therefore, farms' efficiency has been declining over time, being faster in the Northeast and the slowest in the East.

An important feature of the stochastic production function is the marginal product of land, labor, fertilizer and capital. Table 3 contains the marginal products, evaluated at the sample mean of the data, and the associated standard errors computed using the Delta method.[3] Marginal products of all four inputs clearly differ across the four regions, and, hence, there is not indication of resource allocation meeting an efficiency standard across regions in China over 1995-1999. Among the inputs, the marginal product of fertilizer is most similar across the regions. The marginal product of land and capital are highest in the Northeast. The marginal product of labor is low, and we cannot reject that the marginal product is zero, except for the North, which indicates the existence of excessive labor input use. This result is largely consistent with conclusions in Wan and Cheng (2001).

Lin (1992) used data during the transition period (1978-1984) and reported estimates of output-input elasticities of 0.49, 0.21, 0.15, and 0.06 for land, labor, fertilizer and capital, respectively. These values are somewhat close to our estimates for the East, but quite different from those for other regions. Our estimates of production elasticities show the continued (to varying extents) important role played by land in Chinese agricultural production, as well as mixed indications on other inputs across regions. The economies of scale elasticity, evaluated at the sample geometric mean of the inputs, ranges from 0.88 to 1.00 for the four regions, and all 95 percent confidence intervals include unity. Hence, even though the size of Chinese farms is small by Western standards, we cannot reject the hypothesis of a constant return to scale where land, labor, capital and fertilizer are variable.

Technical efficiency scores are reported in table 4. The average technical efficiency score for the North, Northeast, East and Southwest are 0.80, 0.85, 0.73, and 0.69, respectively. Table 5 provides a comparison of the estimated efficiency scores with those obtained in previous studies. Our estimates are generally comparable to those in Li and Zhuang (2000), but lower than those

[3] We also evaluated them at the sample median and obtained similar results.

in other studies. The transformed efficiency indices are standardized and pooled, then regressed on a set of explanatory variables. Table 6 presents estimates of two behavioral farm technical efficiency equations. The baseline model includes regional fixed effects, which allows the four regions to have different mean technical efficiency scores. The second model includes village fixed effects; hence, the baseline model is nested in it. The village effects could capture some of the differences in the village migrant ratio, plot size in the village, and village-specific effects of the decisions of village councils. Hence, we present estimates of both models as a sensitivity check. A Chow-test is also performed, and we cannot reject the null hypothesis that the parameters in the farm technical efficiency equation are the same across the four regions, which is the main reason we adopt the particular methodology employed here.

Both the baseline model and the one including village effects show that a farm household having a member on the village council does not affect significantly technical efficiency. This is at odds with earlier results in Cheng (1998), but since Cheng's study and ours do not overlap in time, the evidence is not contradictory. The earlier positive role of the village officer may have dissipated as China's agriculture modernized and new institutions to support this modernization were developed. Input markets have gained openness, and hence, since the later 1990s, leverage through the village council is no longer necessary for farmers to gain access to variable inputs and machinery. The estimated coefficient for household size is not significantly different from zero at the 5 percent significance level. This may seem surprising at first glance; since it was hypothesized that large households can more easily mobilize labor to meet peak demands at planting and harvesting time. However, in table 3, we showed that the marginal product of labor was low and near zero.

Farmers with more farming experience (measured by the household head's age) have greater farm technical efficiency, consistent with a large amount of information summarized in Huffman (2001). Meanwhile, our results show that little evidence exists to support the common view that households with older heads are less efficient. We also examine the effects of the household head's education, but it is insignificant. This could be due to its correlation with household head age, but an alternative explanation is that the nearly universal primary school education is sufficient for the majority of the farmers to handle the current agricultural production technology in China. However, as Green Revolution and Gene technologies are developed and distributed to farmers at a faster rate, we expect schooling of farmers to be more important to technical efficiency. Mechanization improves efficiency in the baseline model, but is insignificant in model containing village fixed effects model. Hence, there is something about the village that is closely associated with mechanization and affects technical efficiency. We have, however, ruled out a household member being on the village council.

With low marginal products of farm labor, it is not surprising that the estimated coefficient of the village migrant ratio in the technical efficiency equation is positive and statistically significant in both models. Several pathways are possible. First, vibrant labor markets indicate an inflow of information and remittances that could be used to improve farming equipment and technology, and to purchase industrial inputs. Second, if surplus labor can leave the farming sector, the quality of the labor input in agricultural production may be improved. Third, land consolidation is more likely to happen if those left in the village are willing to lease their land to those remaining in agriculture.

The negative coefficient of the SI in the technical efficiency equation indicates that a higher level of land fragmentation reduces efficiency, controlling for number of plots. The number of plots indicator that fall in the third quartile has the largest and most positive impact on technical efficiency. Along with estimates of the other two plot-number indicators, this suggests that technical efficiency increases when the number of plots increases from the first quartile to the second and from the second to the third, but decreases when the number of plots increases from the third to the highest quartile. This complicated pattern could be attributable to that plot numbers being correlated with household size and total cultivated area. However, the main evidence is that technical inefficiency is negatively related to land fragmentation measured in SI.

6. Conclusions

This paper has examined farm level technology and the technical efficiency of farms in China, a country with millions of small farms. We showed that the parameters of the translog stochastic frontier production function were significantly different across regions in China but that the parameters of the technical efficiency function were the same after standardizing the efficiency index. We showed that marginal products of land, labor, capital and fertilizer differed significantly across regions, and they are not efficiency allocated. In addition, excessive labor seems to exist in Chinese agriculture, giving a very low marginal product. Even with many small farms, we cannot reject the null hypothesis of a constant return to scale in China's agriculture.

Several conclusions can be drawn based on the results. First, we are concerned with overuse of industrial inputs in the East and potentially inefficient use of capital input in the North. Second, our results reveal that farms in the North and Northeast of China in the late 1990s were, on average, relatively efficient, while those in the East and Southwest lagged behind. Third, using machinery and eliminating land fragmentation, in general, bring efficiency gains for Chinese farms, suggesting a change in the land tenure system to facilitate land consolidation. Last, institutional innovations could benefit China's agriculture by making it easier for labor to leave the farming sector.

More research remains to be done in order to gain a better understanding of factors that affect the production efficiency of Chinese agricultural sector, including research on the effects of land quality and scale efficiency. Regional disparity is another intriguing topic to explore using approaches such as spatial econometrics.

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Table 1. Descriptive statistics

Variable	North		Northeast		East		Southwest	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
#Observations	887		476		733		542	
Output (RMB Yuan)	4232.06	5849.83	8009.22	10887.91	5870.69	7278.39	2454.45	2160.15
Land (Mu)	10.21	7.72	18.74	14.35	11.67	7.53	6.47	2.56
Labor (Man-day)	236.89	152.08	255.74	190.47	291.75	197.70	356.58	228.99
Fertilizer (RMB Yuan)	679.14	861.68	917.52	1949.32	1088.67	914.10	328.45	189.62
Capital (RMB Yuan)	601.92	1192.22	569.05	851.68	581.74	633.46	234.52	580.59
Village Migrant Ratio	0.07	0.13	0.05	0.10	0.08	0.13	0.11	0.14
Percentage of Male Labor	0.53	0.22	0.61	0.23	0.51	0.17	0.51	0.20
Household Size	4.18	1.20	4.16	1.11	4.32	1.66	4.34	1.37
Village Officer Dummy	0.06	0.24	0.03	0.16	0.08	0.26	0.03	0.16
Simpson Index (land fragmentation)	0.71	0.18	0.55	0.23	0.58	0.24	0.77	0.16
# plots (quartile 2)	0.31	0.46	0.37	0.48	0.42	0.49	0.19	0.40
# plots (quartile 3)	0.20	0.40	0.14	0.35	0.14	0.34	0.22	0.41
# plots (quartile 4)	0.24	0.43	0.01	0.11	0.07	0.26	0.46	0.50
Head Education > Junior High School	0.55	0.50	0.49	0.50	0.71	0.45	0.27	0.44
Head Age (31-60 yrs old)	0.84	0.37	0.90	0.30	0.94	0.24	0.83	0.38
Head Age (≥61 yrs old)	0.08	0.27	0.03	0.17	0.02	0.15	0.04	0.19
Mechanized (Dummy)	0.21	0.41	0.07	0.25	0.54	0.50	0.16	0.37

Table 2. Maximum likelihood estimates of the Chinese farm stochastic production frontier by region, 1995-1999

Inputs	North		Northeast		East		Southwest	
	Par. Est.	S.E.	Par. Est.	S.E.	Par. Est.	S.E.	Par. Est.	S.E.
Constant	9.064	1.64	9.467***	2.07	9.517***	1.77	1.842	3.43
ln(land)	2.484***	0.69	1.234	1.01	3.248***	0.80	−0.113	1.25
ln(labor)	0.595	0.53	−1.480*	0.86	−1.991***	0.72	1.324	1.08
ln(fertilizer)	−2.223***	0.55	0.389	0.52	−0.253	0.57	0.766	0.87
ln(capital)	−0.261	0.32	−0.569	0.44	−0.044	0.34	−0.451	0.40
$(\ln(\text{land}))^2$	0.214*	0.12	−0.037	0.14	0.259**	0.12	0.135	0.15
$(\ln(\text{labor}))^2$	−0.267***	0.08	0.123	0.10	0.367***	0.11	−0.001	0.11
$(\ln(\text{fertilizer}))^2$	0.164***	0.05	0.076***	0.03	0.110	0.08	0.127*	0.08
$(\ln(\text{capital}))^2$	0.054*	0.03	−0.017	0.02	−0.027	0.02	−0.094***	0.02
ln(land)*ln(labor)	0.368***	0.15	−0.080	0.19	−0.467***	0.16	0.039	0.20
ln(land)*ln(fertilizer)	−0.794***	0.14	−0.070	0.11	−0.264*	0.15	0.097	0.14
ln(land)*ln(capital)	0.019	0.07	0.075	0.09	0.071	0.08	−0.176	0.11
ln(labor)*ln(fertilizer)	0.379***	0.12	−0.112	0.12	−0.128	0.14	−0.418***	0.15
ln(labor)*ln(capital)	−0.080	0.07	0.198***	0.08	0.013	0.08	0.229***	0.07
ln(fertilizer)*ln(capital)	0.014	0.06	−0.065	0.05	0.042	0.07	0.074	0.06
Year 1996 Dummy	−0.035	0.08	0.150***	0.06	0.014	0.06	−0.199***	0.08
Year 1997 Dummy	−0.142*	0.08	0.272***	0.06	0.243***	0.07	−0.132	0.08
Year 1998 Dummy	0.070	0.10	0.352***	0.07	0.014	0.08	0.009	0.09
Year 1999 Dummy	0.002	0.13	0.228**	0.10	−0.052	0.10	0.106	0.11
Village Fixed Effects	Yes		Yes		Yes		Yes	
σ^2	1.481***	0.54	1.014***	0.24	1.565***	0.47	3.699***	0.67
Γ	0.658***	0.13	0.876***	0.03	0.837***	0.05	0.912***	0.02
μ	−1.974	1.60	−1.885***	0.46	−2.289*	1.35	−3.674***	0.56
η	−0.185*	0.10	−0.354***	0.14	−0.086*	0.05	−0.194***	0.04
loglikelihood	−997.2		−224.5		−616.2		−539.3	

Note: *** indicates significance level at 0.01, ** indicates significance level at 0.05, and * indicates significance level at 0.1.

Table 3. Input-output elasticities and marginal effects by region

	North		Northeast		East		Southwest	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Elasticity								
land	0.35	0.10	0.60	0.09	0.43	0.09	0.38	0.09
labor	0.48	0.07	−0.06	0.08	0.12	0.07	0.05	0.07
fertilizer	0.23	0.07	0.16	0.05	0.14	0.07	0.35	0.06
capital	−0.06	0.04	0.22	0.03	0.19	0.04	0.01	0.03
scale	1.00	0.07	0.92	0.07	0.88	0.07	0.78	0.07
Marginal product								
land	82.02	23.29	223.68	33.79	168.87	33.60	109.09	27.02
labor	4.71	0.71	−1.48	1.95	1.87	1.17	0.27	0.43
fertilizer	0.94	0.28	1.42	0.46	0.64	0.33	2.11	0.37
capital	−0.56	0.33	4.07	0.60	1.89	0.37	0.16	0.44

Notes: Evaluated at the geometric means of the inputs and output; standard errors are calculated using the Delta method.

Table 4. Summary statistics of efficiency scores by province

Region	Province	Obs	Mean	S.D.	Min	Max
North		887	0.80	0.10	0.26	0.96
	Hebei	640	0.80	0.10	0.26	0.94
	Shanxi	247	0.79	0.11	0.42	0.96
Northeast		476	0.85	0.12	0.14	0.98
	Heilongjiang	363	0.84	0.12	0.14	0.98
	Liaoning	113	0.86	0.13	0.31	0.98
East		733	0.73	0.16	0.14	0.96
	Anhui	299	0.76	0.11	0.38	0.93
	Jiangsu	288	0.70	0.20	0.14	0.95
	Shandong	146	0.74	0.13	0.36	0.96
Southwest		542	0.69	0.19	0.02	0.94
	Sichuan	402	0.68	0.20	0.02	0.94
	Yunnan	140	0.73	0.13	0.23	0.93

Table 5. Comparison of estimated efficiency scores with those obtained in previous studies

Author(s)	Data type	Time	Product	Location	Efficiency
Liu & Zhuang (2000)	Household	1990	Cropping	Sichuan	0.553
				Jiangsu	0.773
Xu & Jeffrey (1998)	Household	1985-1986	Hybrid Rice	Jiangsu	0.850
			Convention Rice	Jiangsu	0.940
Wang et. al. (1996)	Household	1991	Agriculture	China	0.621
Tian & Wan (2000)	Provincial	1983-1997	Early Indica Rice	China	0.954
			Late Indica Rice		0.941
			Mid Indica Rice		0.946
			Japonica		0.905
			Wheat		0.862
			Corn		0.853
This study	Household	1995-1999	Cropping	North	0.80
				Northeast	0.85
				East	0.73
				Southwest	0.69

Table 6. Regression of pooled transformed efficiency indices on explanatory variables

	Baseline		Village effects	
	Coef.	S.E.	Coef.	S.E.
Constant	2.580***	0.114	2.799***	0.162
Village Migrant Ratio	0.065***	0.020	0.094**	0.048
Village Officer	0.035	0.082	0.061	0.081
Household Size	0.014	0.014	−0.013	0.015
Head Age (31−60 yrs old)	0.352***	0.068	0.301***	0.071
Head Age (≥61 yrs old)	0.334***	0.107	0.284**	0.112
Mechanized (Dummy)	0.118**	0.048	−0.036	0.065
Simpson Index	−0.436***	0.146	−0.455***	0.158
# Plots (quartile 2)	0.185***	0.063	0.235***	0.067
# Plots (quartile 3)	0.432***	0.078	0.511***	0.082
# Plots (quartile 4)	0.294***	0.089	0.495***	0.101
Year 96 Dummy	−0.159***	0.056	−0.260***	0.055
Year 97 Dummy	−1.129***	0.051	−0.537***	0.055
Year 98 Dummy	−1.550***	0.054	−0.797***	0.055
Year 99 Dummy	−0.259***	0.056	−1.074***	0.057
Region 2 Indicator	−0.529***	0.056		
Region 3 Indicator	−0.787***	0.056		
Region 4 Indicator	−1.052***	0.056		
Village Fixed Effects	no		yes	
Adjusted R^2	0.3900		0.4150	

Note: *** indicates significance level at 0.01, ** indicates significance level at 0.05, and * indicates significance level at 0.1.