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China Economic Review 19 (2008) 287–296
China Economic Review

Efficiency and technology gap in China's agriculture: A regional meta-frontier analysis

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Received 14 June 2006; accepted 18 March 2007

Abstract

This paper utilizes a unique county-level dataset to examine technical efficiency and technology gap in China's agriculture. We classify the counties into four regions with distinctive levels of economic development, and hence production technologies. A meta-frontier analysis is used. We find that although the eastern counties have the highest efficiency scores with respect to the regional frontier but the northeastern region leads in terms of agricultural production technology nationwide. Meanwhile, the mean efficiency of the northeastern counties is particularly low, suggesting technology and knowledge diffusion within region might help to improve production efficiency and thus agricultural output.

JEL classification: D24; N55; O13
Keywords: China's grain production; County-level; Meta-frontier; Stochastic production frontier; Technical efficiency

1. Introduction

The increasing demand for grain in China due to income and population growth has invited debates on how well China can feed its population in the future. The extant literature has seen a great deal of discussions on whether viable options remain for increasing agricultural production in China. The role of technical and allocative efficiency was investigated in Chen and Huffman (2006), Mao and Koo (1997), Wang, Cramer, and Wailes (1996), and many others (see, also, a discussion in Abdulai & Huffman, 2000).

Many of the aforementioned studies have used micro-level data sets. Estimates derived from aggregate datasets may produce different results and, hence, different policy implications (Carter, Chen, & Chu, 2003). Studies based on

Abbreviations: GVAO, Gross Value of Agricultural Output; LP, Linear Programming; OLS, Ordinary Least Square; QP, Quadratic Programming; SSB, State Statistical Bureau; TE, Technology Efficiency; TGR, Technology Gap Ratio; SPF, Stochastic Production Frontier.

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1043-951X/$ - see front matter
doi:10.1016/j.chieco.2007.03.001

aggregate statistics could derive inferences and recommendations about regional policies. Provincial statistics of China have been extensively used, see, e.g., the influential paper of Lin (1992) on household responsibility system, and Fan and Zhang (2002) on productivity and inequality. On the other hand, Herrmann-Pillath, Kirchert, and Pan (2002) argue that provincial aggregation might not reflect the exact regional inequality of development for China and propose to use prefecture-level data. Chen and Huffman (2006) use county-level dataset to investigate patterns of technical efficiencies in China's agriculture. Meanwhile, an important feature of agricultural production, namely regional variation, arises when aggregate statistics are used. With a size similar to that of the United States and spanning from frigid to torrid zones, China displays significant geographical variation, i.e., soil quality, climate, precipitation, and pests, across the country. Yang (1996) finds that for respective crops, factor productivities are generally higher in the major producing areas than those in the fringe areas, likely due to more suitable natural conditions and higher level of specialization. The economic institutions and levels of economic development also vary across China, e.g., see Krusekopf (2002) for a discussion of the diversity in land tenure arrangements.

To further understand the impact of regional variation on the estimation of efficiency in agricultural production, it is desirable to examine how agricultural production technologies differ across regions. Production frontiers may shift due to variation in farming technologies and economic institutions. Therefore, traditional efficiencies operating under a common production frontier are not comparable with those operating under different production frontiers.

Recent regional studies suggest that there are four grand regions in China, i.e., Northeast, East, Central, and West, differing from each other in geography, natural endowment, and most importantly, the level of economic development.[3] Ignoring the variation across the regions could lead to biased estimates of the frontier production function and efficiency scores, and hence misleading policy implications. The objective of this paper is to provide new evidence on production efficiency and technology gap in China using a meta-frontier methodology based on a unique county-level data set in 1999. A meta-frontier methodology is an overarching function that encompasses the deterministic components of the stochastic frontier production functions operating under the different technologies involved (Battese, Rao, & O'Donnell, 2004). The model enables the calculation of comparable efficiencies and estimation of technology gaps for production under different technologies relative to the potential technology available to the economy as a whole.

The rest of this paper is organized as follows. Section 2 formulates the econometric modeling strategy. Section 3 describes the data. Section 4 presents the empirical findings. The last section concludes.

2. Econometric methodology

The goal of our analysis is to assess how efficient China's counties are in their agricultural production using a recently developed variant of stochastic production frontier model, which dates back to Meeusen and van den Broeck (1977) and Aigner, Lovell, and Schmidt (1977).

A stochastic frontier model assuming a truncated normal distribution of the non-negative random term can be expressed as: $Y_i=f(x_i,\beta)\ e^{(V_i-U_i)}$, $i=1,\ldots,N$, where Y_i is the output (or its natural logarithm) of the i-th county; x_i is a $k\times 1$ vector of the input quantities (or their natural logarithms) of the i-th county; β is a conformable parameter vector. V_is are the random disturbance terms that are assumed to be i.i.d. $N(0,\sigma_{\mathrm{v}}^2)$. They are incorporated in the model to reflect the random disturbance that is independent of U_is, which are non-negative random terms that represent technical inefficiencies in production. They are assumed to be i.i.d. and truncated at zero of the $N(\mu,\sigma_{\mathrm{u}}^2)$ distribution. The relationship between U_i and the output-oriented technical efficiency (TE) is $\mathrm{TE}^i=\exp(-U_i)$.

To accommodate the potential regional variation of agricultural production frontiers and obtain comparable technical efficiencies for the counties, the meta-frontier analysis proposed in Battese et al. (2004) is used in this study. The meta-frontier production function is a frontier function that envelops all frontiers of individual regions/groups. Fig. 1 presents an illustration of a simple case with one input. At a given input bundle, the technology gap ratio (TGR) is defined as the highest possible output within the region divided by the highest possible output at the meta-frontier. The technical efficiency relative to the meta-frontier is defined to the real output of a county divided by the highest possible output at the meta-frontier. The meta-frontier can be estimated by finding a function that best envelops the

[3] Expert opinions have resulted statements regarding regional economic development in Chapter 19–20 in the National Economic and Social Development Eleventh Five-year Plan, see e.g., http://politics.people.com.cn/GB/59496/4208570.html.

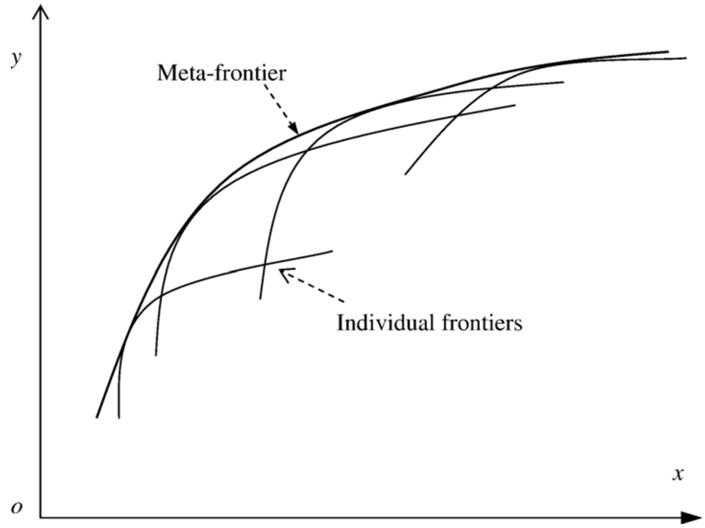

Fig. 1. Illustration of meta-frontier and individual frontiers.

deterministic components of the estimated stochastic frontiers for the different groups. The meta-frontier production function is a frontier function that envelops all the frontiers of individual regions/groups j.

$$Y_i^* = f(x_i, \beta^*) = \mathrm{e}^{x_i \beta^*}, \qquad i = 1, 2, \cdots, N \tag{1}$$

where β^* denotes the vector of parameters for the meta-frontier function such that:

$$x_i \beta^* \geq x_i \beta_{(j)}, \qquad j = 1, 2, \cdots, J. \tag{2}$$

Note that:

$$Y_i = \mathrm{e}^{-U_{i(j)}} \times \frac{\mathrm{e}^{x_i \beta_{(j)}}}{\mathrm{e}^{x_i \beta^*}} \times e^{x_i \beta^* + V_{i(j)}}. \tag{3}$$

Therefore, the TGR is defined as:

$$\mathrm{TGR}_i = \frac{\mathrm{e}^{x_i \beta_{(j)}}}{\mathrm{e}^{x_i \beta^*}} \tag{4}$$

and the technical efficiency relative to the meta-frontier is:

$$\mathrm{TE}_i^* = \mathrm{TE}_i \times \mathrm{TGR}_i. \tag{5}$$

Battese et al. (2004) estimate the parameters of the meta-frontier function by minimizing the sum of absolute deviation and squared deviation, respectively, of the values on the meta-frontier function from the group-specific frontiers at the observed input levels. The squared deviation approach leads to the following quadratic programming (QP) problem:

$$\min_{\beta^*} L^* = \sum_{i=1}^{N} (x_i \beta^* - x_i \hat{\beta}_{(j)})^2 \tag{6}$$

$$\text{s.t. } x_i \beta^* \geq x_i \hat{\beta}_{(j)}, \qquad j = 1, 2, \cdots, J. \tag{7}$$

And the absolute deviation approach leads to the linear programming (LP) problem:

$$\min_{\beta^*} L^* = \sum_{i=1}^{N} |x_i\beta^* - x\hat{\beta}_{(j)}| \tag{8}$$

$$\text{s.t. } x_i\beta^* \geq x_i\hat{\beta}_{(j)}, \qquad j = 1, 2, \cdots, J. \tag{9}$$

In this paper, we follow Battese et al. (2004) in choosing the squared deviation, which assigns higher weights to large deviations. The TGR and TE* can be calculated based on the resulted estimates of β^* and the individual frontier estimates.

3. Data

China comprises 31 provinces (municipalities or autonomous regions), which consist of 2159 counties (or its equivalence) in the 1990s.[4] Data for this study are obtained from a county-level social and economic survey conducted by the Statistical Bureau of China in 1999 (SSB, 2000). The data set contains information regarding agricultural production and socioeconomic variables in 1999. Our final sample contains 2002 counties, after excluding 157 missing observations (one or more critical statistics not reported in the SSB dataset) that mostly are in Xizang (Tibet) and Qinghai provinces. Agricultural technology in these areas could be distinct from those in other counties due to the high altitude. Hence, we believe the exclusion of these observations does not introduce concerns over data truncation but instead can reduce potential estimation bias.

A recent classification puts all Chinese provinces in four grand regions: East (Beijing, Tianjing, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan), Northeast (Liaoning, Jilin, Heilongjiang), Central (Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan), West (Neimenggu, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang).[5] The Northeast provinces are relatively homogenous in terms of soil quality, climate and economic conditions thus grouped together. The classification of the remaining three regions in general reflects three levels of economic development. Provinces in the East see high rates of economic growth and higher income per capita. The agricultural sector in these provinces constitutes a smaller proportion of the gross domestic product than it does in other areas, mostly due to higher levels of industrialization. Meanwhile, economic development has rendered many opportunities for rural residents in the East, and facilitated the information flow in these areas as well. In terms of economic development in the late 1990s, the Central provinces fall behind those in the East while provinces in the West generally lag even further.[6]

Different levels of economic development may induce disparities in information transmission, technology adoption, and even institutions. In addition, the technology diffusion may follow a geographic contiguous pattern. Therefore, the oft-observed disparity in economic development across the four regions motivates us to evaluate the difference in the agricultural technologies, i.e., whether they have distinctive production frontiers from each other, and hence this should be accommodated when measuring production efficiencies. A natural question is whether the observations within a region conform to a uniform production technology. With different climate and soil conditions, it is unlikely that farmers apply same production technology throughout a region. Irrigation systems may vary within a region in response to these conditions. Unfortunately, the relevant data are not available to us at this time. Nonetheless, with a given level of economic development, our assumption is that an abstract production function would capture how changes in inputs and/or input mixes would impact agricultural output, rather than correspond to a material production technology. Our approach is built upon those of previous studies that estimate a production frontier for the entire China, e.g., Yao, Liu, and Zhang (2001), and intend to improve the estimation with the meta-frontier analysis incorporating the

[4] The number of counties may vary over time due to administrative changes.

[5] See, e.g., http://www.china-county.org/zonglan/zonglan19.asp.

[6] Lu and Song (2004) show that the ratio of per capita GDP between the eastern and central regions increased from 2.0 in 1980 to 2.27 in 2000 while the ratio of per capita GDP between the east and western regions increased from 2.21 in 1980 to 2.89 in 2000.

Table 1
Summary statistics of the China county-level agricultural production dataset at the year 2000

Variable	Symbol	Unit	National	East	Central	West	Northeast
Output (agricultural GVAO)	y	10^4 Yuan	69,297.14	103,440.40	62,415.96	44,617.29	85,389.39
			(57,843.33)	(63,862.00)	(51,925.97)	(39,355.61)	(65,445.94)
Labor use	z_1	10^4 person	15.16	15.99	16.49	13.96	11.18
			(11.39)	(9.35)	(13.29)	(11.18)	(7.13)
Sown area	z_2	Hectare	71,656.32	74,237.05	77,703.66	55,685.72	101,916.90
			(50,870.80)	(41,072.99)	(55,743.04)	(40,317.77)	(72,635.12)
Mechanical power	z_3	10^8 W	21.57	35.33	21.30	10.86	19.73
			(22.26)	(28.81)	(21.23)	(8.91)	(11.80)
Fertilizer use	z_4	Ton	18,972.43	25,791.01	20,023.93	11,445.79	21,909.29
			(18,516.82)	(20,781.06)	(19,539.96)	(11,359.30)	(18,506.61)
Geomembrane	z_5	Ton	329.64	345.35	275.53	375.21	332.96
			(505.25)	(475.71)	(340.73)	(674.83)	(372.94)
Population density	x_1	10^4 person/km^2	0.31	0.48	0.32	0.20	0.14
			(0.28)	(0.29)	(0.27)	(0.25)	(0.11)
Non-agricultural GDP per capita	x_2	10^4 Yuan	0.36	0.61	0.28	0.23	0.37
			(0.37)	(0.48)	(0.20)	(0.31)	(0.25)
Available credit per capita	x_3	Yuan	0.33	0.44	0.28	0.25	0.53
			(0.32)	(0.44)	(0.24)	(0.24)	(0.27)
Number of teachers per hundred	x_4	Person	0.90	0.89	0.91	0.85	1.05
			(0.23)	(0.19)	(0.20)	(0.27)	(0.22)
Observations			2002	526	694	632	150

Source: Authors' tabulation based on data extracted from the State Statistical Bureau Website.

effect of regional economic development on production technologies. Meanwhile, modeling the variation in production technology and ecological conditions within a region should be attempted whenever it is possible.

The sample statistics for the agricultural input and output variables are reported in Table 1. Five inputs are considered in this study, i.e., sown area (hectare), labor use (10^4 person), chemical fertilizer (ton), mechanical power (10^8 W), and geomembrane use.[7] The output is measured as the gross value of agricultural output (GVAO) in RMB Yuan. Note that although the credibility of past GVAO statistics had been questioned in the past, the quality of recent Chinese statistics has been significantly improved and is believed to be satisfactory; see Fan and Zhang (2002) for an application of regional production study using GVAO statistics. A typical county has 71,656 ha of sown area and employs around 152 thousand agricultural labors, uses 216 million watt equivalent mechanical power, applies 19 thousand metric tons of chemical fertilizer, and produces 693 million RMB Yuan worth of agricultural products.[8] Input usage varied across China due to the large geographic area spanned and different levels of economic development. Labor input has a relatively small dispersion while fertilizer usage and mechanic power employed display significant variation across counties.

4. Results

We first fit stochastic production frontier (SPF) models to the pooled dataset and the individual grand regions. A likelihood ratio test suggests rejection of the frontier model for the East, which has the highest geographic variation. Hence, we fit an ordinary least square (OLS) model for the East. It is widely acknowledged that the eastern counties have better factor markets and enhanced infrastructure, such as transportation. Hence, the eastern counties are likely to push their agricultural production to the frontier in the region. Frontier models cannot be rejected for the other grand regions and the pooled sample. The parameter estimates can be found in Tables 2 and 3. We test the hypothesis that the pooled frontier model is true (all counties conform to a same stochastic production frontier) with the separate estimation

[7] The quantity of chemical fertilizers is calculated by converting the gross weight into weight containing 100% effective component (i.e., 100% nitrogen content in nitrogenous fertilizer, 100% phosphorous pentoxide contents in phosphate fertilizer, 100% potassium oxide contents in potash fertilizer).

[8] One RMB Yuan has been approximately $0.12 for the last decade though there was a slight appreciation in 2005.

Table 2
MLE estimates of the SPF and meta-frontier (QP/LP) for China

	National (SPF)		Meta-frontier (QP)		Meta-frontier (LP)	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Constant	13.108***	1.039	22.397***	5.472	39.261***	12.144
lnz1	1.130***	0.245	1.447**	0.721	2.139*	1.149
lnz2	−0.519	0.331	−2.116	1.914	−5.332*	2.772
lnz3	0.960***	0.264	−0.505	0.700	1.567	1.816
lnz4	−1.009***	0.285	−0.083	1.148	−1.042	1.754
lnz5	−0.063	0.179	−0.700	0.624	−0.049	0.770
$(\ln z1)^2$	0.035**	0.016	−0.015	0.037	0.026	0.054
$(\ln z2)^2$	0.007	0.031	0.082	0.168	0.276	0.187
$(\ln z3)^2$	0.014	0.012	−0.054**	0.026	−0.034	0.043
$(\ln z4)^2$	0.037***	0.015	0.052	0.061	0.163*	0.083
$(\ln z5)^2$	0.004	0.005	0.037	0.025	0.051**	0.026
lnz1 * lnz2	−0.099***	0.035	−0.172	0.115	−0.163	0.142
lnz1 * lnz3	0.029	0.032	−0.074	0.091	0.015	0.126
lnz1 * lnz4	0.005	0.036	0.089	0.097	−0.035	0.128
lnz1 * lnz5	−0.014	0.015	0.029	0.055	0.032	0.070
lnz2 * lnz3	−0.051	0.039	0.096	0.115	−0.119	0.205
lnz2 * lnz4	0.090**	0.042	−0.025	0.182	−0.070	0.212
lnz2 * lnz5	0.008	0.023	0.120*	0.069	0.091	0.079
lnz3 * lnz4	−0.068***	0.025	0.030	0.070	0.019	0.115
lnz3 * lnz5	0.048***	0.015	−0.047	0.059	−0.037	0.081
lnz4 * lnz5	−0.021	0.017	−0.098	0.063	−0.150*	0.080
σ^2	1.114***	0.096				
γ	0.885***	0.016				
μ	−1.986***	0.256				

Notes: Asterisks ***, **, and * indicate statistically significant at 0.01, 0.05, and 0.1 significance levels, respectively.

of the four grand regions (OLS for the East and frontier models for the rest) as the alternative model. The likelihood ratio statistic is distributed as a chi-square with degree of freedom as 69.[9] We reject the null hypothesis with a p-value less than 0.001.

The estimates of the meta-frontier estimations (both quadratic programming and linear programming) are presented in Table 2 as well as the pooled estimates of the stochastic frontier model. The standard deviations of the meta-frontier estimates are calculated using parametric bootstrapping as Battese et al. (2004) suggested. The number of replications used is 2000 times. The relatively sparse statistical significance appears to be of concern. However, two issues are relevant. First, the bootstrapping procedure might have introduced some upward biases in the variance estimates (see, e.g., Liou & Yu, 1991). Second, since we have only four regions, it is not truly surprising that there could be some variability in defining the meta-frontier. Partitioning the whole country into more sub-regions may help but it may undermine the estimation of the regional frontier estimates. Furthermore, our primary interest is to examine whether there are differences in technological gap and technical efficiency of the four grand regions recently formed and defined. We also want to point out that a more parsimonious Cobb–Douglass specification has better significance level but it is well-known that trans-log form is a more flexible functional form. Trans-log specification presents a better approximation of the frontiers and hence improves the model fit, see discussions of trans-log in, e.g., Christensen, Jorgenson, and Lau (1971, 1973). Table 3 presents the parameter estimates of the production frontier by region.

Estimated technical efficiencies with respect to the regional frontiers and the meta-frontier, together with estimated TGRs, are presented in Table 4. The value of TGRs ranges from 0.627 to 1. Counties in the Northeast region generally lead in terms of technology gap ratio and have the smallest variation of TGR. Provincial-wise, the average TGR of Liaoning of the Northeast is the highest (0.985). However, technology efficiencies of northeastern counties are lower

[9] The degree of freedom is calculated as the sum of numbers of parameters of all four individual frontiers (93) minus the number of parameters for a frontier estimated full sample (24).

Table 3
Frontier estimates by region

	East		Central		West		Northeast	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Constant	4.950	4.188	11.646***	1.696	10.952***	1.798	26.431**	11.553
lnz1	−0.183	1.321	−0.174	0.359	1.250***	0.414	5.607***	1.958
lnz2	2.292*	1.310	0.033	0.499	−1.222**	0.523	−1.811	2.582
lnz3	3.054***	0.589	−1.023**	0.491	0.683	0.499	−1.985	2.240
lnz4	−3.313***	0.745	0.045	0.420	−0.006	0.429	−0.824	1.774
lnz5	0.954**	0.384	−1.240***	0.325	0.332	0.228	−2.359*	1.212
$(\ln z1)^2$	0.068	0.088	0.032	0.021	0.121***	0.032	0.059	0.111
$(\ln z2)^2$	−0.297***	0.094	0.001	0.046	0.116***	0.046	0.085	0.180
$(\ln z3)^2$	0.120***	0.033	−0.006	0.020	0.009	0.016	−0.319	0.212
$(\ln z4)^2$	0.002	0.038	0.062**	0.028	0.004	0.016	0.195	0.132
$(\ln z5)^2$	0.015*	0.008	−0.004	0.009	−0.015**	0.006	0.078**	0.033
lnz1 * lnz2	0.488***	0.178	0.151**	0.069	−0.195***	0.060	−0.523*	0.268
lnz1 * lnz3	0.071	0.067	−0.246***	0.062	0.000	0.051	0.464*	0.280
lnz1 * lnz4	−0.514***	0.106	−0.101	0.064	0.081	0.053	−0.017	0.227
lnz1 * lnz5	−0.066	0.041	0.047*	0.028	−0.032	0.021	−0.150	0.124
lnz2 * lnz3	−0.352***	0.086	0.121*	0.070	−0.076	0.063	0.300	0.282
lnz2 * lnz4	0.479***	0.086	−0.084	0.070	−0.013	0.057	−0.190	0.228
lnz2 * lnz5	−0.093*	0.055	0.093***	0.037	−0.056*	0.031	0.355***	0.118
lnz3 * lnz4	−0.061	0.054	0.048	0.048	0.006	0.030	0.103	0.276
lnz3 * lnz5	0.090***	0.023	−0.013	0.028	0.042**	0.021	−0.250	0.167
lnz4 * lnz5	−0.021	0.039	0.014	0.032	0.041**	0.020	−0.133	0.124
σ^2			2.128***	0.266	0.384	0.265	0.224**	0.109
γ			0.981***	0.005	0.774***	0.150	0.892***	0.091
μ			−2.890***	0.426	−1.090	1.555	0.260	0.409

Notes: The estimates for the East area are based on OLS since the frontier specification has been rejected. Asterisks ***, **, and * indicate statistically significant at 0.01, 0.05, and 0.1 significance levels, respectively.

than those in the East and Central and lead to a very low average technical efficiency relative to the meta-frontier. Meanwhile, the TGRs of the East, Central and West are lower than that of the Northeast whilst counties in the West have the lowest TGRs. Counties in the Central have the lowest average technical efficiency and a medium level TGR. The West has the lowest average TGR ratio hence its average efficiency is reduced from 83% when compared relative to the frontier within West to 76% when compared to the meta-frontier. The fact that we cannot reject the null hypothesis that there is no one-sided error term in the frontier estimation for the East suggests that counties in the East

Table 4
Summary statistics of TEs and TGRs by region

Region	Statistics	Mean	S.D.	Min	Max
National	TE_i	0.803	0.194	0.002	1.000
	TGR	0.938	0.032	0.627	1.000
	TE*	0.752	0.181	0.002	1.000
East	TE_i	1.000	0.000	1.000	1.000
	TGR	0.940	0.023	0.817	1.000
	TE*	0.940	0.023	0.817	1.000
Central	TE_i	0.661	0.205	0.002	0.947
	TGR	0.945	0.022	0.829	1.000
	TE*	0.625	0.195	0.002	0.907
West	TE_i	0.829	0.075	0.446	0.943
	TGR	0.918	0.038	0.627	1.000
	TE*	0.761	0.074	0.430	0.913
Northeast	TE_i	0.655	0.167	0.172	0.937
	TGR	0.976	0.018	0.890	1.000
	TE*	0.639	0.163	0.170	0.913

Table 5
Summary statistics of TEs and TGRs by province

	TE_i		TGR		TE*	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Anhui	0.692	0.177	0.951	0.021	0.658	0.170
Beijing	1.000	0.000	0.938	0.013	0.938	0.013
Chongqing	0.807	0.104	0.949	0.009	0.765	0.096
Fujian	1.000	0.000	0.942	0.026	0.942	0.026
Gansu	0.816	0.078	0.895	0.054	0.731	0.085
Guangdong	1.000	0.000	0.951	0.022	0.951	0.022
Guangxi	0.813	0.103	0.933	0.026	0.758	0.095
Guizhou	0.840	0.054	0.929	0.025	0.781	0.053
Hainan	1.000	0.000	0.945	0.028	0.945	0.028
Hebei	1.000	0.000	0.929	0.029	0.929	0.029
Helongjiang	0.657	0.166	0.968	0.020	0.636	0.162
Henan	0.647	0.211	0.944	0.019	0.611	0.198
Hubei	0.660	0.194	0.955	0.013	0.631	0.187
Hunan	0.639	0.239	0.953	0.017	0.609	0.227
Jiangsu	1.000	0.000	0.940	0.013	0.940	0.013
Jiangxi	0.649	0.233	0.954	0.016	0.620	0.224
Jilin	0.665	0.177	0.980	0.014	0.652	0.175
Liaoning	0.643	0.161	0.985	0.012	0.634	0.158
Neimenggu	0.672	0.170	0.945	0.030	0.635	0.162
Ningxia	0.804	0.078	0.906	0.038	0.727	0.069
Qinghai	0.842	0.065	0.869	0.056	0.731	0.064
Shaanxi	0.648	0.194	0.937	0.023	0.607	0.182
Shandong	1.000	0.000	0.944	0.010	0.944	0.010
Shanghai	1.000	0.000	0.950	0.022	0.950	0.022
Shanxi	0.689	0.204	0.929	0.016	0.639	0.189
Sichuan	0.843	0.066	0.916	0.041	0.772	0.072
Tianjin	1.000	0.000	0.946	0.011	0.946	0.011
Xinjiang	0.828	0.068	0.918	0.030	0.760	0.061
Yunnan	0.831	0.066	0.920	0.025	0.765	0.064
Zhejiang	1.000	0.000	0.944	0.023	0.944	0.023

are close enough to the frontier and thus reach the highest possible efficiency score (100%).[10] However, the 94% average TGR reduces its average efficiency to 94% relative to the meta-frontier, although still leading among the four regions. In Table 5, we present technical efficiency scores by province. However, it serves as a rough description of the efficiency distribution and does not provide an absolute or accuracy ranking of the provinces. Hence precautions should be taken in interpreting the result.

Note that there are several counties with particularly low efficiency scores—29 counties with efficiency scores lower than 0.2 and one of them lower than 0.01. They could be results of unexpected shocks or mere inefficiency in the particular year. We have re-estimated the model with these counties excluded and obtained similar results, likely thank to the relatively robustness of SPF to outliers (compared with Data Envelopment Analysis). In addition, Battese et al. (2004) observe some small values of efficiency scores with respect to the regional frontier, coupled with very low technology gap ratio, lead to values of overall efficiency lower than 0.01. Hence, we chose to keep the original results instead of the set of results obtained with the least efficient counties excluded.

We have made an attempt to explain the efficiency indexes and TGRs with exogenous variables. However, with scant information on institution and socio-demographic variables, we are only able to examine the relationship of these indexes and population density and non-agricultural GDP per capita. Population density could be related to infrastructure while non-agricultural GDP per capita correlates with the development of industrial and service sector. Several other variables such as teacher–population-ratio as a proxy for education stock and available credit per capita were added in a set of expanded regressions. However, we caution on the potential endogeneity of these variables. Empirically, Tobit models were adopted following Chavas, Petrie, and Roth (2005) to accommodate the upper

[10] Even we impose a stochastic frontier model on the sample of the East, we obtain efficiency indices that are very close to 1.

Table 6
MLE estimates of Tobit models

Dependent variable	TE^{it}		TGR		TE*	
Population density	0.299***	0.256***	0.046***	0.041***	0.194***	0.152***
	(0.035)	(0.038)	(0.005)	(0.005)	(0.025)	(0.027)
Population density squared	−0.121***	−0.098***	−0.024***	−0.023***	−0.088***	−0.068***
	(0.023)	(0.024)	(0.003)	(0.003)	(0.016)	(0.017)
Non-agriculture GDP per capita	0.220***	0.281***	−0.005***	−0.010***	0.094***	0.133***
	(0.019)	(0.024)	(0.002)	(0.003)	(0.011)	(0.015)
Available credit per capita		−0.096***		0.011***		−0.052***
		(0.024)		(0.003)		(0.016)
Number of teachers per hundred		−0.034		−0.013***		−0.051***
		(0.027)		(0.003)		(0.019)
Constant	0.699***	0.749***	0.930***	0.940***	0.674***	0.733***
	(0.010)	(0.027)	(0.001)	(0.004)	(0.007)	(0.019)

Note: Asterisks ***, **, and * indicate statistically significant at 0.01, 0.05, and 0.1 significance levels, respectively.

censoring. Table 6 presents the MLE estimates of the Tobit regressions with TE^{it}, TGR, and TE* as dependent variable. While regressions on TE^{it} and TGR should be interpreted as partial effects, the regression on TE* is the composite effect of the explanatory variables on technical efficiency relative to the meta-frontier. There is a consistent non-linear relationship between the indexes and the population density. However, it is surprising that non-agricultural GDP per capita is negatively associated with TGR, suggesting that industrial and service development did not spill over to the development of agricultural technology although its net effect on TE* is positive, likely due to a positive relationship between non-agricultural sector development and agricultural technical efficiency. The expanded specification yields a plausible positive effect of credit availability on TGR but negative effects on TE^{it} and TE*, which remain puzzling for us. The teacher-population-ratio has an unexpectedly negative effect on TE* through TGR. One of the possibilities is that economic development may be associated with a well-educated labor force or an influx of labors, which leads to relatively less pressure on pre-college education. However, the results on credit availability and education from the expanded specification probably should be interpreted with caution since there is no clear causal pathway amid many possibilities. Meanwhile, the coefficient estimates of non-agricultural GDP per capita, population density and its squared term are stable with respect to the specification change. Additional policy variables, such as institutional variables, infrastructure, and better measurement of education stock, would benefit analyses of such kind and provide more insights.

5. Discussions

This study has provided some interesting results on the county-level agricultural technical efficiency in China. Apart from the traditional frontier analysis, the meta-frontier analysis divides the production efficiency into two parts: one caused by the inefficiency relative to the subgroup, and one caused by the technology gap between the subgroup and the full sample. The empirical results provide more policy implications. First, although technology diffusion within the East has enabled all counties achieved the highest possible output with respect to the regional production frontier (suggested by the rejection of an additional asymmetric error term), they still have room to advance their frontier compared to the counties in the Northeast (indicated by the existence of technology gap between the Eastern counties and the meta-frontier). Second, counties in the West could improve their technical efficiency via advancing the production frontier by adopting technology from other grand regions as well as improving technical efficiency through technology diffusion within the region, although it is complicated by the fact that irrigation and weather conditions may interfere with the agricultural production in the West. Third, the counties in the Central and Northeast could improve their efficiency through technology/knowledge diffusion within region. That is, there are some counties leading in terms of agricultural technology in these regions but the production technology has not been disseminated well within these regions. A well-functioning agricultural extension system may help to facilitate technology diffusion and hence reduce technical inefficiencies. Lastly, although we have invited caution in interpreting the ranking of provincial/county efficiency indices, it provides us an opportunity to identify some counties that are relatively efficient and could serve as case studies.

In summary, we have two suggestions. First, more attention should be paid to agricultural extension systems to disseminate agricultural technology and know-how between and within the regions. Second, when the ecological difference has limited the diffusion of agricultural technology, institutional variables, such as factor markets and rural governance, should be further examined (Zhang, Fan, Zhang, & Huang, 2004). Whether efforts should be invested in following the leading counties within the group or within the nation, which could be determined by examining the efficiency scores and technology gap ratios. Meanwhile, our attempt to explain the technical efficiency indexes and technical gaps is a preliminary analysis. A caveat we want to acknowledge is that the current data lacks information on land quality, climate, and other factors that might be used to explain technical efficiencies. Whether county-level efficiency estimates could be severely affected remains unknown, though the symmetric disturbance term absorbs certain amount of unobserved factors. This also calls for further data collection efforts. More research remains to be done in order to gain a better understanding of factors that affect technical efficiency and technology gap in China's agriculture.

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