Technical Efficiency Under Producer's Individual Technology: A Metafrontier Analysis

Xiaobing Wang*, Heinrich Hockmann**

*Center for Chinese Agricultural Policy,
Institute for Geographical Sciences and Natural Resources Research,
Chinese Academy of Sciences
Tel +86-10 64888673/64888979
Fax +86-10 64856533
Email: xbwang.ccap@igsnrr.ac.cn;

Institute of Agricultural Development in Central and Eastern Europe (IAMO), Germany.
Tel: +49-345-2928225,
Fax: +49-345-2928299,
Email: Hockmann@iamo.de

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ABSTRACT

Differences in resource endowment between regions influence the technologies applied in agriculture and cause location-specific effects on production and technical change. Access to technologies may also differ within regions because producers may apply different technologies in production due to different characteristics. Within this setting, we extend the existing literature by considering that producers face region- and farm-specific production frontiers. The treatment of essentially heterogeneous technical efficiency (TE) is performed following a two-step procedure. First, a random coefficient specification of the production technology is used to measure the interactions of technology adoption with time, input factors and output. Second, linear programming techniques are employed to envelop the optimal level of technology. This procedure is applied to household-level data from eastern, central and western provinces in China. Our results provide evidence that technical efficiency is significantly affected by farm heterogeneity. This factor influences TE directly as a producer-specific input, and indirectly through interaction with observable inputs such as land, labor, capital and intermediate inputs. Our results also prove the assumption that farming technology exhibits region-specific characteristics. Furthermore, there is a disparity of TE across provinces that narrows over the study period and is driven by the shifts of production to the metafrontier.

JEL classification: D24, N55, O13

Keywords: technical efficiency, metafrontier, random coefficient model, Chinese agriculture

1 INTRODUCTION

An increased level of efficiency that better employs scarce resources in agricultural production is an important indicator of a nation's transition process from an agricultural-based, labor-intensive economy to one increasingly based on industries and services. China's agriculture is unique in that it is characterized by an extremely egalitarian distribution of cultivated land, which means that there are more than 200 million rural households, each of which cultivate less than 0.55 hectares (NSBC 2005). There is little reason to believe that China could expand the average household's holding of land (through the rapidly-growing land rental markets) (Kung 2002), and even if it did, the literature suggests that there are small positive economies of scale in Asian agriculture (Trueblood and Coggins 2003). In addition, the country's extension system for expanding new technology in production has collapsed (Hu et al 2009). Concerned with national food security, China's political agenda has always placed a high priority on finding methods to motivate small farmers to improve their efficient use of input resources, and thus contribute to the rise of productivity.

Technical procedures using stochastic frontier (SFA) or data envelopment analysis (DEA) are generally familiar to studies that evaluate the contribution of technical efficiency (TE) change to total factor productivity (TFP) (e.g. Bonds and Hughes 2007). Regarding the application of SFA in China, several studies conclude that although TE has improved greatly since institutional reforms have been introduced, regional TFP growth differs largely due to regional variations of TE in both magnitude and direction (Fan 1991; Wu 1995; Kalirajan et al 1996). These conclusions have also been verified by applying the DEA approach (Mao and Koo 1997). However, all of these studies rely on provincial quantile production data, which restricts the analysis to the provincial or regional level and hides the variation of TE and technology within provinces. Thus, policy implications based on provincial- or regional-level studies may not necessarily be appropriate at lower administrative levels (Pender et al 1999). Using household-level data, Brümmer et al (2002) found that the difference in productivity prior to and after the 1990s resulted from differences in TE in the two periods, which was brought about by land policy and the frequent adjustment of market policies. Because this study is limited to households in the Zhejiang province, it is difficult to generalize its findings to households across different economic, social and geographic locations.

Parallel theoretical and methodological developments on efficiency analysis concentrate on the identification of determinants of inefficiency such as location-specific factors of production and the behaviour of producers. Using household-level data, Wang et al (1996) and Liu and Zhuang (2000) found that under the constraint of market distortions, TE could mainly be explained by farm-specific effects. Based on crop-specific production functions, Huang and Kalirajan (1997) and Tian and Wan (2000) presented evidence that TE is responsive to crop varieties and planting systems, which are under the influence of technological improvement. Zhang et al (2011) concluded that technical efficiency and its variation across provinces are influenced by local land reallocation policies and institutional settings. The basic assumption of the abovementioned studies is that all producers operate under a given technology, and thus face the same production efficiency frontier.

Differences in resource endowment among regions influence the adoption of technology and the variation of TE. This idea has been inlayed into a meta-frontier function to allow measuring TE for each group of producers under group-specific production frontiers (Hayami 1969; Hayami and Ruttan 1970, 1971; Battese and Rao 2002; Stewart et al 2009). This has inspired a number of studies on agricultural production across regions within a country as well as across countries (Battese et al 2004; Bravo-Ureta et al 2007; Chen and Song 2008). However, it is observed that distinct producers even within a local region may have access to different technologies due to different farm and household characteristics. Metafrontier analysis generally aggregates the producer-specific technologies into several composite measures, and fails to capture the impact of heterogeneous technologies available to each producer in a certain region. To account for farm-specific factors, random parameter models (RPM) can be used. This class of models was introduced by Tsionas (2002) and extended by Alvarez et al (2003, 2004). In these models, heterogeneity is captured by an unobservable variable that is simulated by suitable estimation procedures.

The goal of our paper is to extend the existing literature in two dimensions. First, we use a random coefficient model to analyze the magnitude and direction of TE change under farm heterogeneity and region-specific frontiers. This approach also allows us to assess whether regional variation of output is due to farm inefficiencies or is caused by the various sources of input heterogeneity such as capital vintages, land quality and human capital, etc. Second, we rely on a metafrontier approach to investigate the significance of regional sources of technical efficiency.

The rest of this paper is organized as follows. Section 2 specifies the random parameter model and the metafrontier function. Section 3 presents the data source and descriptive statistics of variables used in the estimations. Empirical results are presented and discussed in Section 4. The fifth section concludes the paper with a summary and a discussion of policy implications.

2 THEORETICAL BACKGROUND

The theoretical framework is developed within a panel data methodology, with $i = 1,\ldots,N$ farms and $t = 1,..,T$ observations per farm. The first step concerns the estimation of region-specific production functions. We model production in an input augmentation framework, i.e., we define effective inputs (x^e) as:

$$\mathbf{x}^e{}_{it} = \mathbf{x}_{it} e^{\boldsymbol{\tau}_{xt} t} e^{\boldsymbol{\mu}_{xi} \theta_i} . \tag{1}$$

Here, $\boldsymbol{x}_{it}$ is a vector[1] of observable inputs and t accounts for technology change (TC). The symbols $\boldsymbol{\tau}_t$ and $\boldsymbol{\mu}_i$ represent parameter vectors, while θ_i represents a non-observable farm-specific factor. It can be expected that this input is a surrogate for several determinants of farm production usually not observable, like input quality, farm structure and organization, as well as socioeconomic characteristics of the farm households. The unobservable component is used in an attempt to measure the level and the complex interaction of these determinants.

In this general representation, the unobservable input can have two specifications. First, $\theta_i = m_i^*$ indicate that farms operate at the optimal level of the specific factor. Second, however, farmers may not fully exploit the productive capabilities of the unobserved factor, in this case $\theta_i = m_i < m_i^*$. Under this assumption, the difference $m_i - m_i^*$ can be regarded as a generic component of technical efficiency (please see equation 6 below).

The maximum level of production (y*) is given when $\theta_i = m_i^*$:

$$y_{it}^* = f\left(\mathbf{x}_{it}^e ; m_i^*\right) . \tag{2}$$

Actual production is:

$y_{it} = f\left(\mathbf{x}_{it}^e ; m_i\right)$, or

$$y_{it} = f\left(\mathbf{x}_{it}^e ; m_i^*\right) * TE_{it} \text{, with } TE_{it} = \frac{f\left(\mathbf{x}_{it}^e ; m_i\right)}{f\left(\mathbf{x}_{it}^e ; m_i^*\right)} . \tag{3}$$

In the empirical application we assume a translog production function:

$$\ln f\left(\mathbf{x}^e{}_{it} ; m_i^*\right) = \alpha_0 + \boldsymbol{\alpha}_{\mathbf{x}}' \ln \mathbf{x}_{it}^e + \frac{1}{2} \ln \mathbf{x}_{it}^e{}' \mathbf{A}_{\mathbf{xx}} \ln \mathbf{x}_{it}^e . \tag{4}$$

Rearranging terms provides:

$$\begin{aligned} \ln f\left(\mathbf{x}^e{}_{it} ; m_i^*\right) = {} & \alpha_0 + \alpha_m m_i^* + \frac{1}{2} \alpha_{mm} m_i^{*2} + \left(\alpha_t + \frac{1}{2} \alpha_{tt} t + \alpha_{tm} m_i^*\right) t \\ & + \left(\boldsymbol{\alpha}_{\mathbf{x}} + \boldsymbol{\alpha}_{\mathbf{x}t} t + \boldsymbol{\alpha}_{\mathbf{x}m} m_i^*\right)' \ln \mathbf{x}_{it} + \frac{1}{2} \ln \mathbf{x}_{it}' \mathbf{A}_{\mathbf{xx}} \ln \mathbf{x}_{it} \end{aligned} . \tag{5}$$

A similar relationship holds for $\theta_i = m$. The various parameters associated with t and m_i are functions of $\alpha_{\mathbf{x}}, \mathrm{A}_{\mathbf{xx}}$ as well as $\tau_{\mathbf{x}t}$, and $\mu_{\mathbf{x}i}$. Given this specification of the production function, TE is given by:

[1] In this paper vectors and matrices are represented by bold small and capital letters, respectively.

$$lnTE_{it} = \gamma_0 + \gamma_t t + \boldsymbol{\gamma}_{\mathbf{x}}{}' ln\,\mathbf{x}_{it}, \text{ with } \gamma_0 = \alpha_m (m_i - m_i^*) + \tfrac{1}{2}\alpha_{mm}\left(m_i^2 - m_i^{*2}\right)$$

$$\gamma_t = \alpha_{tm}(m_i - m_i^*) \tag{6}$$

$$\boldsymbol{\gamma}_{\mathbf{x}} = \boldsymbol{\alpha}_{\mathbf{x}m}{}'(m_i - m_i^*)$$

According to (6), TE consists of four components. The first represents a time-invariant firm-specific effect, whereas the other terms reflect the interaction of m^* and m with time and inputs. An interesting term in the expression is γ_t, since it provides information about the change of inefficiency over time, and thus, reveals whether there are catching up or falling behind processes.

Equations (3) and (6) constitute a system that cannot be estimated directly, since neither m nor m^* are known. However, the estimation can be conducted when the system is transformed into a standard frontier model:

$$ln\, y_{it} = f\left(\mathbf{x}_{it}^e; m_i^*\right) - u_{it} + v_{it} \tag{7}$$

where u_{it} is defined by (6) and $f\left(\mathbf{x}_{it}^e; m_i^*\right)$ is given by (5).

Equation (7) can be estimated using maximum simulated likelihood (Greene 2005) by making the conventional assumption regarding v_{it} and u_{it}. Thus, v_{it} represents a random error term with $v_{it} \sim N(0, \sigma_V)$, and u_{it} is the technical inefficiency with $u_{it} \sim N^+(0, \sigma_u)$. Moreover, m_i^* is assumed to obey a standard normal distribution, e.g. $m_i^* \sim N(0,1)$. When estimating the RPM, the parameters associated with m_i^* are identified up to their sign. Moreover, given the distributional assumption about m^* they must be regarded as input-specific standard deviations (Greene 2005). Thus, the impact of m_i^* on production is not uniquely identified.[2] Alvarez et al (2003, 2004) extended the standard approach by assuming that production reacts positively to an increase of the unobservable component, e. g.:

$$\frac{\partial f\left(\mathbf{x}_{it}^e; m_i^*\right)}{\partial m_i^*} \geq 0\,. \tag{8}$$

This restriction identifies the signs of the corresponding parameters; in addition, farm-specific values of unobserved heterogeneity can be estimated by (Alvarez et al 2004):

$$\hat{E}\left[m_i^* \mid \mathbf{X}_i, \boldsymbol{\delta}\right] = \frac{\frac{1}{R}\sum_{r=1}^{R} m_{i,r}^* \hat{f}\left(\mathbf{y}_i^k \mid t, m_{i,r}^*, \mathbf{X}_i, \hat{\boldsymbol{\delta}}\right)}{\frac{1}{R}\sum_{r=1}^{R} \hat{f}\left(\mathbf{y}_i^k \mid t, m_{i,r}^*, \mathbf{X}_i, \hat{\boldsymbol{\delta}}\right)} \tag{9}$$

where $m_{i,r}^*$ is a draw from the population of m_i^*, R is the number of the draw, and $\hat{f}$ denotes the portion of the likelihood function for firm i, evaluated at the parameter estimates and the current value of $m_{i,r}^*$. The vector $\hat{\boldsymbol{\delta}}$ represents a vector of estimated parameters. The capital

[2] The reason is that m^* and the associated parameters enter the model multiplicatively.

letter in case of inputs indicates that the likelihood function is evaluated for all observations of firm *i*.

Given the estimated level of m_i, efficiency scores can be computed by (Jondrow et al 1982; Alvarez et al 2004):

$$-\ln TE_{ij} = E\left[u_{it} \mid \varepsilon_{it}, m_i^*\right] = \frac{\sigma\lambda}{(1+\lambda)^2}\left[\frac{\phi\left(-\lambda\frac{\varepsilon_{it} \mid m_i^*}{\sigma}\right)}{\Phi\left(-\lambda\frac{\varepsilon_{it} \mid m_{i\,i}^*}{\sigma}\right)} - \lambda\frac{\varepsilon_{it} \mid m_i^*}{\sigma}\right] \qquad (10)$$

with $\lambda = \sigma_u / \sigma_v$, $\sigma^2 = \sigma_u{}^2 + \sigma_v{}^2$ and $\varepsilon_{it} = v_{it} - u_{it}$.[3]

The second step involves estimating the metafrontier function. By definition, the metafrontier function cannot fall below the deterministic portion of the group-specific stochastic frontier models. Moreover, it must be ensured that the estimated metafrontier best envelops the deterministic components for different groups. Battese et al (2004) proposed a method called the minimum sum of absolute deviations to identify the envelope. Following this approach, the metafrontier function is estimated by solving the following LP problem:

$$\underset{\beta^*}{\mathrm{Min}} \sum_{i=1}^{I}\sum_{t=1}^{T}\left|\ln f\left(\mathbf{x}_{it};\boldsymbol{\delta}^*\right) - \ln f\left(\mathbf{x}_{it};m_{i,k}^*,\hat{\boldsymbol{\delta}}_k\right)\right| \equiv \sum_{i=1}^{I}\sum_{t=1}^{T}\left|\ln f\left(\mathbf{x}_{it};\boldsymbol{\delta}^*\right)\right| \qquad (11)$$

subject to $ln\ f\left(\mathbf{x}_{it};\boldsymbol{\delta}^*\right) > ln\ f\left(\mathbf{x}_{it};m_{i,k}^*,\hat{\boldsymbol{\delta}}_k\right)$

where *ln f* is the logarithm form of the production function in (2), $\hat{\boldsymbol{\delta}}_k$ is a vector of parameter estimates obtained from the stochastic group-specific frontier, and $\boldsymbol{\delta}^*$ contains the parameters of the metafrontier function to be estimated.

Once the values of $\boldsymbol{\delta}^*$ are estimated, the technology gap ratio (TGR) can be estimated. TGR for the *i*-th producer in the *k*-th group at the *t*-th time period can be obtained by:

$$TGR_{it}^k(X,Y) = \frac{f\left(\mathbf{x}_{it};m_{i,k}^*,\boldsymbol{\delta}_k\right)}{f\left(\mathbf{x}_{it};\boldsymbol{\delta}^*\right)} \qquad (12)$$

Then, a measure of the total output-oriented technical efficiency $TE_{it}^o(X,Y)$ is obtained by:[4]

$$TE_{it}^o(X,Y) = TGR_{it}^k * TE_{it}^k \qquad (13)$$

Figure 1 assists in providing an intuitive interpretation of our procedure. We basically distinguish three levels of production: farm, regional, and national. The farm-specific technologies are considered by m*, the indicator of farm heterogeneity. Both the farm level and the regional level are estimated by equation (7). The next step consists of determining the

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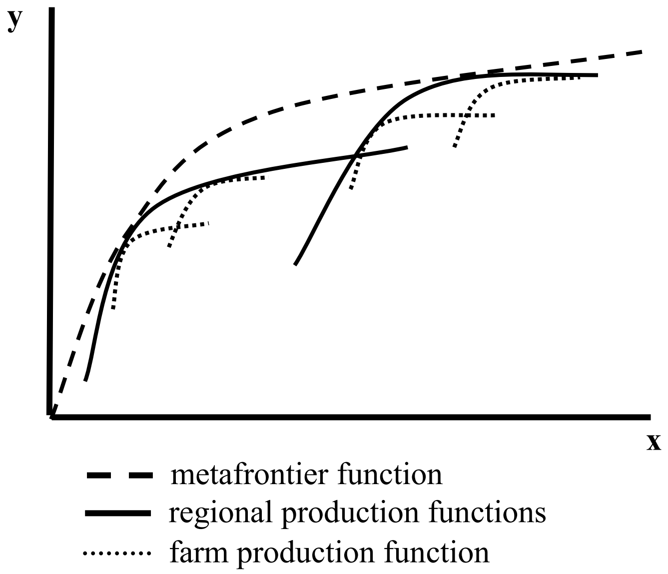
[3] The model can be estimated using Limdep 9.0 or NLogit 4.0. The routine also provides the values of the unobserved components and efficiency.

[4] Here TE_{it}^k denotes group-specific (*k*) technical efficiency provided by the first step for individual producers (*i*) and time (*t*).

metafrontier function as an envelope of regional production functions. This is done by using equation (11).

Figure 1: Illustration of Meta-frontier, regional and individual frontier functions



3 DATA SOURCES and DESCRIPTIVE STATISTICS

The database used in this study was drawn from a fixed-point survey across Zhejiang, Hubei, and Yunnan provinces that is conducted annually by the Chinese Ministry of Agriculture. These three provinces were chosen to reflect the diversity of Chinese agricultural production. Zhejiang province is one of the richest provinces in the East, Hubei province represents the central middle-income region, and Yunnan province belongs to West China and is one of the poorest regions in the country.[5] The sample collection proceeded in a stratified manner. Initially, every county was stratified by annual net income per capita into upper, middle, and lower groups. Representative villages in each group were chosen according to geography (plain, hilly, or mountainous area), location (city, suburb, or rural), and economic characteristics defined as mainly agriculture, forestry, animal husbandry, fishery or others. Household data from the respective villages were then randomly selected. To maintain longitudinal household information, the same households were interviewed each time the survey was conducted. If the household was dropped from the survey and was not recorded on the household list in the village, a new sample household was recruited from the same village with another ID and remained in the survey for the following years.[6] These characteristics allowed us to establish a balanced panel data from 1995 to 2002, in which 133 households were attained from Zhejiang, 160 households from Hubei and 215 households from Yunnan. The household data contained detailed information on agricultural production operations.

Table 1. Descriptive statistics of variables by provinces, 1995-2002

Variable	Symbol	Unit	No. of Observation	Mean	Standard Deviation	Minimum	Maximum
				Zhejiang			

[5] Per capita gross regional product in Zhejiang, Hubei and Yunnan in 2004 amounts to 23,942 RMB, 10,500 RMB and 6,733 RMB, respectively (NSBC, 2006).

[6] Households dropped from the survey due to the emigration of the whole family from the village to the urban area or other towns or villages, or the family members died after several years of being in the survey.

Output	Y	Yuan	1064	15592.1	28431.6	110.2	231667.0
Labor	A	Day	1064	294.4	237.9	2.0	3600.0
Land	L	Mu	1064	4.7	2.6	0.1	22.0
Capital	K	Yuan	1064	2697.8	7728.0	30.0	85300.0
Intermediate	V	Yuan	1064	10230.4	25063.9	14.0	229611.0
				Hubei			
Output	Y	Yuan	1280	5370.9	3393.3	253.0	41163.9
Labor	A	Day	1280	382.1	149.9	17.0	1106.0
Land	L	Mu	1280	13.7	273.5	0.6	9793.0
Capital	K	Yuan	1280	626.3	663.6	14.0	9700.0
Intermediate	V	Yuan	1280	1841.4	2046.2	4.0	36956.0
				Yunnan			
Output	Y	Yuan	1720	6506.1	3201.0	154.7	43090.0
Labor	A	Day	1720	610.8	260.3	20.0	1816.0
Land	L	Mu	1720	6.2	3.3	0.7	29.7
Capital	K	Yuan	1720	1184.9	985.4	14.0	9800.0
Intermediate	V	Yuan	1720	3558.4	2061.0	150.0	28387.0
				All			
Output	Y	Yuan	4064	8527.3	15407.4	110.2	231667.0
Labor	A	Day	4064	455.9	263.1	2.0	3600.0
Land	L	Mu	4064	8.2	153.5	0.1	9793.0
Capital	K	Yuan	4064	1405.1	4101.7	14.0	85300.0
Intermediate	V	Yuan	4064	4764.4	13364.2	4.0	229611.0

Source: Fixed-point household level data, Ministry of Agriculture (MOA), China.

The dependent variable used in the frontier production functions is the value of output, which aggregates the value of physical products from crops, livestock and other agricultural products. Labor input is defined as total annual working days allocated to agricultural production, forestry, animal husbandry and fishery activities. Land input includes cultivated land, husbandry land and woodland. Capital is taken as the monetary value of farm machines. Intermediate inputs sum up expenditure on chemical fertilizer, pesticides, plastic film and other expenditures involved in production. All value variables in the unit of RMB are normalized at constant 1995 prices.

Descriptive statistics of the variables presented in Table 1 reveal significant variations of output and inputs across provinces. Rural households in Zhejiang, on average, earn more agricultural income using less land and labor, but more capital and intermediate inputs compared to households in Hubei and Yunnan. This might be caused by different resource endowment and farm structures across provinces, indicating that technology adopted by rural households is to a large extent region-specific. This suggests that metafrontier does exist in China's agricultural production. Thus, previous studies that do not account for region-specific technology are perhaps inadequate for modeling Chinese agricultural production.

4 EMPIRICAL RESULTS

The data described in the previous section were used to estimate the stochastic province-specific and pooled production functions shown in equation (7). The stochastic province-specific production functions are estimated using the household data separately for each province, whereas in the pooled estimation, the data from all provinces are considered. The variables used in the model estimation were normalized by their respective geometric means to avoid numerical difficulties in the maximum likelihood estimations, and to facilitate the interpretation of the parameter estimates.[7] The estimated coefficients for each model are presented in Table 2.

Standard variations of composite error terms ($\sigma = \sigma_v + \sigma_u$) are approximately 0.20 in Hubei, 0.28 in Yunnan and 0.35 in Zhejiang, implying that a large part of output variation is explained by the model. However, not only the size but also the structures of the two error terms vary among the provinces. The importance of inefficiency compared to the random effects on output variability is expressed in term λ, which is equal to the relation of the σ_u and σ_v. Thus, values larger than 1 imply that inefficiency is more pronounced than random influences. This holds for Zhejiang and Hubei, while in Yunnan both sources have approximately the same value.

Further differences among the provinces exist with respect to the impact of TC. While agriculture in Zhejiang and Yunnan benefited from technical progress, production in Hubei is characterized by accelerated technological progress (a_t and $a_{tt} < 0$). On average, Yunnan benefited more from TC than Zhejiang. However, in the latter we observed an accelerating growth of production possibility while the growth rate in Yunnan was decreasing. In all provinces technical change was capital saving ($\alpha_{kt} < 0$), and intermediate inputs and labor using ($\alpha_{at} > 0$, $\alpha_{vt} > 0$). Land saving TC was estimated for Yunnan and Hubei, while in Zhejiang it was land using.

The estimates of $\alpha_{\#}$, with # = A, L, K, V are the production elasticities at the sample mean. Our results indicate that there is no joint pattern of average elasticities of physical inputs among regions. The two most important factors are labor and intermediate inputs, the latter of which accounted for approximately 40% of production. The production elasticities of labor are approximately 0.4 in Zhejiang and Hubei, but in Yunnan it is significantly smaller at approximately 0.15. This structure of the elasticities is consistent with the level of regional development. Since Yunnan is less developed than the other regions, it can be expected that the opportunity costs of labor are relatively low in this region, which implies that farms allocate comparatively more labor to agricultural production than farms in other regions. The lowest production elasticity is observed for capital, with values at about 0.02. This holds for all regions. However, contrary to labor this is not an indicator that capital is abundant, but rather scarce. Since an elasticity is the ratio of marginal and average product, a small elasticity can also be attributed to a high average factor productivity. This will be the case when the factor is scarce, for example capital in Chinese agriculture. The production elasticity of land also differs significantly across regions and ranged from about 0.18 in Hubei to 0.08 in Zhejiang and .1 in Yunnan. The sum of the individual production elasticities provides the elasticity of scale. This indicator ranges from about 0.9 in Zhejiang and Hubei to about 0.75

[7] Due to this procedure, the parameter estimates for α_x cannot be directly interpreted as average production elasticities in the group-specific estimations. However, the difference between the estimates and the average production elasticity was rather low. Thus, in order to facilitate comparison between the group-specific and the pooled models, is it appropriate to regard the parameter estimates as fair approximations for the production elasticities.

in Yunnan. This result is also consistent with labor-intensive and capital-extensive production, since economies of scale usually can only be exploited through the adoption and intensive use of new machinery.

Table 2. Parameter estimates for the random coefficient model across provinces and Metafrontier function, 1995-2002

	Random coefficient model								*Metafrontier*
	Zhejiang		*Hubei*		*Yunnan*		*All*		
α_0	0.4492	(0.0290)	0.1397	(0.0149)	0.0802	(0.0173)	0.2912	(0.0101)	0.7421
Impact of technical change									
α_T	0.0092	(0.0085)	-0.0094	(0.0035)	0.0222	(0.0034)	0.0011	(0.0021)	-0.0161
α_{TT}	0.0033	(0.0054)	-0.0019	(0.0025)	-0.0096	(0.0027)	-0.0038	(0.0020)	0.0122
α_{AT}	0.0128	(0.0092)	0.0196	(0.0066)	0.0031	(0.0072)	0.0186	(0.0030)	0.0220
α_{LT}	0.0161	(0.0118)	-0.0125	(0.0062)	-0.0008	(0.0056)	0.0018	(0.0041)	0.0259
α_{KT}	-0.0138	(0.0042)	-0.0035	(0.0024)	-0.0044	(0.0025)	-0.0114	(0.0017)	-0.0710
α_{VT}	0.0065	(0.0075)	0.00003	(0.0041)	0.0070	(0.0043)	0.0028	(0.00280	0.0176
Mean of the random process (average production elasticities)									
α_A	0.4166	(0.0329)	0.3778	(0.0206)	0.1576	(0.0185)	0.1768	(0.0082)	0.1838
α_L	0.0834	(0.0289)	0.1849	(0.0184)	0.1000	(0.0162)	0.0847	(0.0070)	0.1030
α_K	0.0493	(0.0115)	0.0272	(0.0084)	0.0400	(0.0098)	0.0344	(0.0035)	0.0217
α_V	0.4120	(0.0200)	0.3802	(0.0129)	0.4362	(0.0137)	0.4666	(0.0052)	0.3742
Coefficients of unobservable factor									
α_{0M}	0.1826	(0.0152)	0.0784	(0.0067)	0.2269	(0.0087)	0.0680	(0.0044)	
α_{TM}	-0.0081	(0.0050)	-0.0088	(0.0024)	0.0165	(0.0028)	0.0059	(0.0021)	
α_{AM}	0.0782	(0.0174)	-0.0937	(0.0135)	-0.0805	(0.0155)	0.0007	(0.0071)	
α_{LM}	-0.0478	(0.0219)	0.0376	(0.0110)	0.1278	(0.0129)	0.0115	(0.0083)	
α_{KM}	0.0725	(0.0089)	-0.0213	(0.0061)	0.0120	(0.0070)	-0.0612	(0.0040)	
α_{VM}	-0.1812	(0.0119)	-0.0579	(0.0079)	0.1259	(0.0107)	0.1599	(0.0060)	
α_{MM}	0.1594	(0.0181)	0.0604	(0.0079)	-0.2525	(0.0110)	-0.4132	(0.0084)	

(Next)

Table 2. continued

	Random coefficient model								Metafrontier
	Zhejiang		Hubei		Yunnan		All		
Pure second order effects									
α_{AA}	0.0969	(0.0399)	0.1508	(0.0349)	0.0683	(0.0394)	0.0015	(0.0134)	-0.0352
α_{LL}	-0.0176	(0.0354)	-0.0644	(0.0156)	0.3560	(0.0373)	0.0028	(0.0083)	0.1718
α_{KK}	0.0497	(0.0078)	-0.0028	(0.0085)	-0.0215	(0.0105)	0.0583	(0.0034)	0.2861
α_{VV}	0.1695	(0.0149)	0.1072	(0.0137)	0.2059	(0.0213)	0.1326	(0.0061)	0.2394
α_{AL}	0.0317	(0.0256)	-0.0990	(0.0334)	-0.1453	(0.0345)	0.0187	(0.0105)	-0.1233
α_{AK}	0.0569	(0.0117)	0.0204	(0.0131)	-0.0599	(0.0162)	0.0385	(0.0045)	-0.0152
α_{AV}	-0.1070	(0.0227)	-0.0646	(0.0179)	-0.0157	(0.0274)	-0.0696	(0.0075)	-0.0192
α_{LK}	-0.0385	(0.0169)	-0.0061	(0.0135)	-0.0252	(0.0148)	-0.0682	(0.0068)	0.0996
α_{LV}	0.0322	(0.0165)	0.0565	(0.0200)	-0.0444	(0.0232)	0.0269	(0.0072)	-0.0867
α_{KV}	-0.0365	(0.0080)	-0.0033	(0.0094)	0.0368	(0.0127)	-0.0165	(0.0039)	-0.0910
Efficiency distribution									
σ_v	0.2510		0.1289		0.2007		0.1838		
σ_u	0.3843		0.2277		0.2060		0.2535		
σ	0.4590	(0.0133)	0.4590	(0.0133)	0.2876	(0.0062)	0.3131	(0.0029)	
λ	1.5309	(0.1470)	1.5309	(0.1470)	1.0264	(0.0929)	0.7250	(0.0401)	
LogL	-452.4872		204.4948		-197.851		-1075.278		
Ob.	1064		1280		1720		4064		

Source: Own estimates.
Notes: Figures in parentheses are standard deviation.

Corresponding to restriction (8), production is increasing with m^* in all provinces. Moreover, the vast majority of the coefficients are highly significant. This indicates that agricultural production is strongly affected by determinants that are not contained in the household data. Possible candidates include soil quality and also socioeconomic characteristics such as household size, off-farm labor supply or hired labor input. The combined effects of the unobserved components are rather complex and lead to different impacts on the production elasticities. Thus, the structure of the parameter estimates for $\alpha_{\#M}$, with # = A, L, K, V are quite heterogeneous across regions. However, it is interesting to note that more favorite unobserved components do not necessarily lead to a better exploitation of technical progress and production possibilities. This is only the case in Yunnan ($\alpha_{TM} > 0$), while in the other two regions the opposite effect dominates. This might indicate that technical progress within the latter regions is driven by catching up processors of farms lacking behind, an interpretation that is supported by the low impact of technical change in Hubei and Zhejiang.

Based on the results in Table 2, a likelihood ratio (LR) test was conducted for the null hypothesis that the province-specific frontiers are identical. The test statistics rejected the null hypothesis with a *p*-value less than 0.001, implying that the province-specific frontiers are not the same. Moreover, conclusions regarding the efficiency of agricultural production would also be biased if all observation were evaluated with regard to the wrong reference technology. Therefore, the metafrontier function presented in equation (11) must be estimated. The production elasticities of the metafrontier function are given in the last column of Table 2. The structures of the elasticities are basically the same as those at the regional level, though smaller in size. This is consistent with the presumption that the metafrontier function is the envelope of the regional production functions. Moreover, the production elasticities provided by the metafrontier function vary from the estimates of a pooled estimation (Table 2, Column 7). This holds especially for intermediate inputs whose importance is overestimated by the pooled estimation.

Table 3 presents average TE scores relative to the stochastic region-specific frontier and metafrontier technologies, as well as TGR scores for each province and all the samples by year. TE scores relative to the region-specific technology average 0.84 both in Hubei and Yunnan, and 0.75 in Zhejiang. The differences between average TE scores indicate that farms in Zhejiang are considerably more heterogeneous with respect to exploiting the regional production possibilities than are farms in the other regions. This conclusion is supported by the higher standard variations in TE relative to the region-specific technology, which are relatively small in Hubei and Yunnan but large in Zhejiang, especially during the late 1990s. This suggests that though the farming management in China is simple due to the constraint of inputs endowment, it is comparatively more flexible on farming management practice in Zhejiang than in Yunnan and Hubei.

The high variation of TE in Zhejiang implies the existence of more technologically advanced farms in that region, which in turn are likely to define the interregional production frontier. This conjecture is confirmed by the results of the metafrontier analysis. Table 4 indicates that the TGR of region-specific technology to the metafrontier technology is relatively small in Zhejiang. This reflects the fact that farm households in comparatively rich provinces like Zhejiang adopt more advanced technology for managing farms. Moreover, it has been shown that in Zhejiang, households are more likely to use capital and other intermediate inputs such as fertilizer and pesticide, rather than traditional labor-intensive technology (see Tables 1 and 2).

Turning to TE^o, we found that the relative inefficiency of production is driven by TGR (Equation 10), e.g. the inefficiencies among regions are more pronounced than those within the regions. Average TE scores imply that all of the households in this study were, on average, producing 82% of the outputs that could be potentially produced from the given inputs by using a region-specific technology as a reference; however, only half of them used the metafrontier technology as a reference. TGR is at about 50%, indicating that production could be doubled if farms were able to access the technology given by the interregional frontier. Moreover, looking at the interregional difference of TE^o, the results indicate that Yunnan is in the process of catching up with Zhejiang, e.g. adopting the best regional production technology. In sum, the developments of TE^o and TGR indicate that Chinese agricultural TFP growth can be further promoted through technology and knowledge transfer which will find their expression in the improvement of TE^o.

Table 3. Technical efficiency and technology gap ratio estimates, 1995-2002

	1995	1996	1997	1998	1999	2000	2001	2002	95-02
					Zhejiang				
TE	0.7509	0.7667	0.7945	0.7197	0.7437	0.7655	0.7640	0.7532	0.7573
	(0.0888)	(0.0751)	(0.0785)	(0.1335)	(0.0905)	(0.1072)	(0.1089)	(0.1098)	(0.1024)
TGR	0.5776	0.5797	0.6036	0.4943	0.5802	0.5680	0.5978	0.6099	0.5764
	(0.1779)	(0.1624)	(0.1951)	(0.1910)	(0.1661)	(0.1920)	(0.2028)	(0.2070)	(0.1898)
TE^o	0.4361	0.4418	0.4827	0.3631	0.4330	0.4338	0.4580	0.4564	0.4381
	(0.1521)	(0.1265)	(0.1730)	(0.1673)	(0.1356)	(0.1570)	(0.1699)	(0.1598)	(0.1587)
					Hubei				
TE	0.8505	0.8175	0.8513	0.8497	0.8474	0.8576	0.8322	0.8463	0.8441
	(0.0819)	(0.0934)	(0.0647)	(0.0653)	(0.0666)	(0.0682)	(0.0926)	(0.0725)	(0.0772)
TGR	0.4758	0.4906	0.4854	0.4684	0.4764	0.4619	0.4550	0.4173	0.4664
	(0.1369)	(0.1318)	(0.1300)	(0.1308)	(0.1192)	(0.1218)	(0.1298)	(0.1450)	(0.1323)
TE^o	0.4065	0.4019	0.4157	0.3986	0.4029	0.3968	0.3797	0.3547	0.3946
	(0.1263)	(0.1193)	(0.1203)	(0.1151)	(0.1049)	(0.1119)	(0.1185)	(0.1285)	(0.1193)
					Yunnan				
TE	0.8360	0.8376	0.8534	0.8396	0.8343	0.8442	0.8475	0.8413	0.8417
	(0.0783)	(0.0528)	(0.0451)	(0.0542)	(0.0564)	(0.0514)	(0.0465)	(0.0578)	(0.0563)
TGR	0.3359	0.3743	0.4301	0.4458	0.4583	0.4668	0.4540	0.4525	0.4272
	(0.0888)	(0.0881)	(0.1192)	(0.1261)	(0.1275)	(0.1308)	(0.1467)	(0.1649)	(0.1336)
TE^o	0.2818	0.3140	0.3674	0.3747	0.3824	0.3945	0.3837	0.3817	0.3600
	(0.0817)	(0.0790)	(0.1052)	(0.1107)	(0.1104)	(0.1148)	(0.1233)	(0.1458)	(0.1167)
					All				
TE	0.8183	0.8127	0.8373	0.8114	0.8147	0.8278	0.8208	0.8198	0.8204
	(0.0916)	(0.0788)	(0.0665)	(0.1011)	(0.0818)	(0.0835)	(0.0888)	(0.0882)	(0.0859)
TGR	0.4432	0.4647	0.4929	0.4656	0.4959	0.4918	0.4920	0.4826	0.4786
	(0.1655)	(0.1508)	(0.1616)	(0.1482)	(0.1452)	(0.1534)	(0.1704)	(0.1877)	(0.1617)
TE^o	0.3615	0.3752	0.4128	0.3792	0.4021	0.4055	0.4019	0.3928	0.3914
	(0.1365)	(0.1193)	(0.1384)	(0.1296)	(0.1174)	(0.1272)	(0.1395)	(0.1496)	(0.1335)

Source: Own estimates.
Notes: Figures in parentheses are standard deviation.

5 CONCLUSION

In this study we extend the existing literature by evaluating the impact of farm heterogeneity when the producers in regions may access farm-specific and time-varying technology. Furthermore, producers in different regions face region-specific production frontiers. The consideration of essentially heterogeneous technical efficiency is first estimated in a two-step procedure, a random parameter model followed by a metafrontier production function. Utilizing household-level data from three provinces in China, the applied approach provides new insights into efficiency analysis in general, and efficiency problems faced by Chinese farms in particular. The empirical results presented here highlight three important implications which require special attention when used for evaluating efficiencies.

First, the results from random parameter models provide evidence that technical efficiency is, in addition to the four main physical inputs (labor, land, capital and intermediate inputs), significantly influenced by unobserved farm-specific variables. These variables influence production and TE directly as a producer-specific input, and indirectly through interaction with other observable inputs. Since the impact of the unobservable component is significant, omitting household heterogeneity would result in a biased parameter and thus efficiency estimates. This implies that previous studies that do not account for the unobservable component factors might be inadequate for evaluating TE of China's agricultural production.

Second, farming technology was found to exhibit a region-specific feature. Over time, the nature of technology changes, as indicated by the sign of the time variable being identified as positive in Yunnan and Zhejiang, but negative in Hubei. The regional differences in terms of return to scale can be explained by the different application of physical inputs and interaction of managerial ability through the observable factors. The evidence is as follows: the use of less labor-intensive farming technology in Zhejiang and Hubei than in Yunnan; the use of more land-intensive farming technology in Hubei than in Zhejiang and Yunnan.

Third, our results suggest that there is a disparity in TE across the three provinces, where the narrowing disparity over the study period is driven by shifts of the production to the metafrontier. To further fill the gap across the regions, the Chinese government has prompted the "Western Region Development Strategy" to increase investment and speed up the development of western regions. Furthermore, from 2002, the government began to subsidize grain producers instead of collecting agricultural taxes. Subsidies, although just beginning, are mostly evaluated as being decoupled (Sonntag et al 2005; Huang et al 2011). This is expected to motivate households to increase investment, adopt new technologies and use physical inputs more efficiently in production. The effects of these policies on agricultural production is worthy of further empirical evaluation.

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