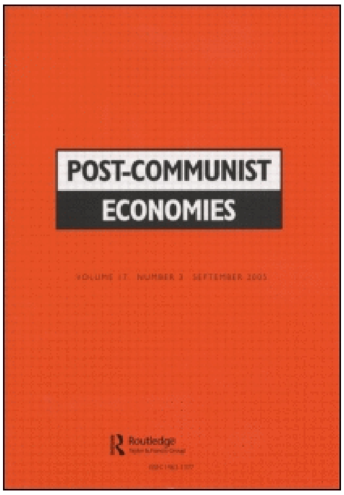

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Agricultural efficiency, technical change and productivity in China

Xiaobing Wang[a]; Supawat Rungsuriyawiboon[b]
[a] Centre for Chinese Agricultural Policy, Chinese Academy of Sciences, Beijing, China [b] Faculty of Economics, Thammasat University, Bangkok, Thailand

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Agricultural efficiency, technical change and productivity in China

Xiaobing Wang[a] and Supawat Rungsuriyawiboon[b]*

[a]*Centre for Chinese Agricultural Policy, Chinese Academy of Sciences, Anwai, Beijing, China, and Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO), Halle (Saale), Germany;* [b]*Faculty of Economics, Thammasat University, Bangkok, Thailand*

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Economic reform in China helped transform the structure and volume of agricultural production and resulted in significant changes in efficiency and productivity. This article measures agricultural technical efficiency (TE) and total factor productivity (TFP) in China by including all producers in different groups operating under their own technologies. A metafrontier function approach is applied using a panel data set on 28 provinces during 1991–2005. The provinces are categorised into advanced and low-technology provinces. Based on the metafrontier estimation, TFP growth is decomposed into TE change (TEC), technical change (TC) and scale efficiency change (SEC). Our major findings indicate that TC contributed most to Chinese agricultural TFP growth throughout the period of study. SEC and TEC exhibited negative effects on TFP growth for the advanced and low-technology provinces respectively. Most of the advanced-technology provinces exhibited higher TE than the low-technology provinces. The comparatively low TE scores in the low-technology provinces imply that the low-technology provinces were operating far from the metafrontier. The results also show that labour and fertiliser still make important contributions to output, and thus improving the quality of farmers and applying modern physical inputs is also crucial to TFP growth.

Food security remains high on China's political economy agenda. Because the nation uses 7% of its land for farming to feed more than 20% of the population in the world, it is thought that it is essential to maintain sufficient levels of food production to feed at least most of its population (Brown 1995). Achieving self-sufficiency, however, will require China to keep its level of productivity high.

Concerns about maintaining productivity are not new. A number of efforts inside and outside China have sought to measure the nation's productivity in agriculture. For example, after the institutional changes and market reforms initiated in 1978 production and productivity rose by 5% and 10% between 1978 and 1985 (McMillan *et al.* 1989, Lin 1992). Using different data sets, Fan (1991) and Huang and Rozelle (1996) also demonstrated that production, yields and overall productivity were strong in the early 1980s. The most recent study that calculated productivity estimated that productivity improvement accounted for around 58% of output growth in the 1990s (Liu and Wang 2005). Clearly, during the 1980s and early 1990s improvements to productivity were instrumental in keeping output high.

*Corresponding author. Email: supawat@econ.tu.ac.th

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Although in the past production and productivity rose very fast, there are several reasons to be concerned about growth in recent years (and in the coming years). Most crucially, in recent years sources of increased inputs, such as the limited land and the shift of rural labour off the farm, are being exhausted (Brown 1995, Jin *et al.* 2007). Therefore, in the future output growth will not be able to rely on mobilising inputs but will require rising productivity. For productivity to rise, this means that either TC, TE or scale economies need to improve.

Unfortunately, there are several concerns about productivity increases – especially if they need to rely on TE or scale economies. China's agriculture is special in the world in that it is characterised by an extremely egalitarian distribution of cultivated land which means that there are more than 200 million rural households which each are cultivating less than 0.55 hectares. With such small farms, each household might be expected to be unable or unwilling to search for new ways to improve their efficiency. However, at the same time, the extension system has been shown to have collapsed (Hu *et al.* 2007). Likewise, even if China could expand its average household's holding of land through the rapidly growing land rental markets (Jin and Deininger 2002), the literature is clear that there are few positive scale economies in Asian agriculture (Trueblood and Coggins 2003).

Therefore, *a priori*, we know that if productivity after the early 1990s was to expand it almost certainly had to rely on the expansion of TC. The record, however, is more mixed on TC. On the one hand, China has traditionally maintained high rates of TC as small farmers have always been eager to adopt new technologies when they were available (Jin *et al.* 2002). However, after the mid-1980s there was at least a period when research expenditure fell (Dong 2000). Although China's officials have begun to invest again (Jin *et al.* 2007), it is possible that this period of relatively low level of investment in agricultural research and development slowed the production of agricultural technologies and this may have undermined rises in productivity.

In the past decade the number of studies evaluating both efficiency and productivity in Chinese agricultural production has kept pace with the evolution of frontier analysis. Two empirical approaches such as a parametric approach known as stochastic frontier analysis (SFA) and a non-parametric approach known as data envelopment analysis (DEA) provide the foundation for the measurement of producers' efficiency and productivity in the literature. The parametric approach of the SFA model has been extensively applied to analyse efficiency and productivity in Chinese agricultural growth by Fan (1991), Wu (1995), Kalirajan *et al.* (1996), Wang *et al.* (1996), Tian and Wan (2000) and Bruemmer *et al.* (2006). However, these studies extended the SFA model to measure producers' efficiency and productivity by assuming that all producers in different groups of a given industry are identical and therefore facing the same best practice frontier.

To take into account inter-group differences in production technologies, Mao and Koo (1997) divided the provinces in China into two groups, advanced and low-technology provinces, on the basis of distinctive levels of economic development and production technologies. Without specifying an *ex ante* functional form and assuming the behaviour of producers, they employed the non-parametric approach of the DEA model to measure producers' efficiency and productivity by including all producers in different groups operating under their own technologies. When all producers in different groups of an industry are operating on different parts of their technologies but have potential access to the same technology, measuring producers' efficiency and productivity without taking into account inter-group differences in production technologies may result in misleading policy implications. Recently Battese *et al.* (2004) proposed a parametric estimation of a metafrontier function to measure the efficiency of producers with regional differences in production technologies.

The overall goal of our study is to address this lacuna in the literature in the following dimensions. First, the parametric estimation of the metafrontier function model is applied to measure TE and TFP growth for the provinces in China. Following Mao and Koo (1997), the provinces are categorised into two groups with distinctive levels of economic development and production technologies. Second, to our surprise, the existing literature, except for Bruemmer *et al.* (2006), accounts for TFP growth considering only two components, TEC and TC, and ignoring the effect from SEC. Bruemmer *et al.* (2006) found negative SEC growth, which is consistent with the general criticism of the land fragmentation problem in Chinese agricultural production (Fleisher and Liu 1992). Rungsuriyawiboon and Lissitsa (2007) conducted a similar study for the transition countries and concluded that SEC had a negligible effect on TFP growth in the Eastern European countries owing to the higher land/labour ratio and flexible land rental system. With small parcels of cultivated land and a thin land rental market, if SEC is still not an essential source of TFP growth, the current land distribution system would be a barrier to the health of the agricultural economy. Considering the possible potential of scale efficiency, this study decomposes TFP growth into the three associated components, TC, TEC and SEC, where TFP growth is measured using the defined metafrontier function. This information is useful for policy makers to design suitable policies to achieve possible TFP growth through the improvement of TC, TEC and SEC. To our knowledge, this is the first application of this technique to empirical metafrontier estimation. Third, a more recent panel data set of 28 provinces covering the time period 1991–2005 is used in this study. Since the start of China's WTO agricultural commitments and subsidising of grain producers in 2002 promoted structural changes in subsequent years, this analysis will reflect a period of more rapid market-oriented reform and structural change in agricultural production in China.

The remainder of this article is organised as follows. The next section presents the theoretical concept of a metafrontier approach, followed by a discussion of the empirical techniques used to estimate efficiency and productivity using the metafrontier analysis. Then we describe the data set and the definitions of all variables. The empirical results are presented and discussed, and the final section summarises our main conclusions.

Model specification

The SFA model originally proposed by Aigner *et al.* (1977) provides the foundation for the parametric measurement of producers' efficiency in the literature. This model assumes that all producers in different groups of an industry are operating with the same production technology. When all producers in an industry have potential access to the same technology but each producer may choose to operate on a different part of their technologies depending on circumstances such as the natural endowment, relative prices of inputs and the economic environment, then producers' efficiency and productivity can be measured using a metafrontier concept. Hayami and Ruttan (1970) initially proposed a metaproduction function which is defined as the envelope of commonly conceived neoclassical production functions. Figure 1 illustrates how the metafrontier function is constructed from different groups of production technologies. Consider an industry consisting of two different groups of production technologies, A and B. A frontier for production technology in group A or T^{A}, which is constructed using the input–output bundles of all producers in group A, is represent by line AA'. Similarly, a frontier for

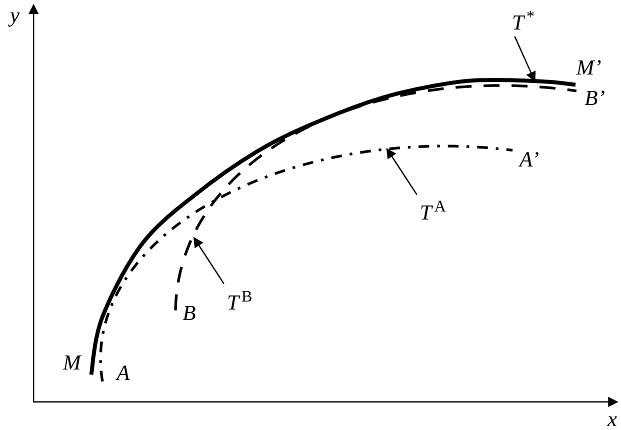

Figure 1. Group-specific frontier and metafrontier.

production technology in group B or T^{B}, which is constructed using the input-–output bundles of all producers in group B, is represent by line BB'. If all producers in groups A and B have potential access to the same technology, the grand frontier which envelops the two group-specific frontiers can be represented by line MM'. This line is referred to as a metafrontier function and the production technology which is constructed from T^{A} and T^{B} is represented by $T*$.

Group-specific technology and metatechnology

Consider a case where all producers of a given industry are categorised into K groups and producers in each group operate with a group-specific technology T^k where $k = 1, \ldots, K$ denotes the index of producer groups. For a data set of each group k consisting of a vector of inputs and outputs for each of the i-th producer where $i = 1, \ldots, I^k$ denotes a producer index. Let the input and output vectors for the i-th producer in the k-th group be denoted $X_i^k = \left(X_{i1}^k, \ldots, X_{iN}^k\right) \in R_+^N$ and $Y_i^k = (Y_{i1}^k, \ldots, Y_{iM}^k) \in R_+^M$ respectively. For any input vector of all producers in the k-th group $X^k \in R_+^N$ and any output vector of all producers in the k-th group $Y^k \in R_+^M$, an input vector X^k is transformed into net outputs Y^k by a production technology T^k. The technology set for the k-th group, technology T^k, which satisfies the axioms presented in Färe *et al.* (1985) is defined as

$$T^k = \{(X^k, Y^k) : X^k \text{ can produce } Y^k\}. \tag{1}$$

Now consider that any input and output vectors of all producers in all groups are given by $X = (X^1 \cup \cdots \cup X^K) \in R_+^N$ and $Y = (Y^1 \cup \cdots \cup Y^K) \in R_+^M$ respectively. If a particular output $Y \in R_+^M$ can be produced using a given input vector $X \in R_+^N$ in any one of the producer groups, a pair (X,Y) belongs to a metatechnology $T*$. $T*$ is defined as the grand technology which envelops all group-specific technologies, $T^1, \ldots, T^K$. The technology set for the metatechnology ($T*$) is defined as

$$T^* = \{(X, Y) : X \text{ can produce } Y \text{ in at least one group–specific technology}\}, \tag{2}$$

where the boundary of the metatechnology set indicates the metafrontier.

A measure of TE defined in Farrell (1957) can be analysed using a distance function. The output distance function of observed data (X^k,Y^k) relative to the group-specific technology T^k is defined as

$$D_o^k(X, Y) = \min\{\mu^k : Y^k/\mu^k \in T^k\}. \tag{3}$$

$D_o^k(X, Y)$ is equal to output-orientated TE, $TE_o^k(X, Y)$, of the observed data (X^k,Y^k) with respect to T^k, so that $0 \leq TE_o^k(X, Y) = D_o^k(X, Y) \leq 1$. Similarly, the relationship between the output-orientated TE and output distance function of the observed data (*X*,*Y*) relative to *T** is defined as $0 \leq TE_o^*(X, Y) = D_o^*(X, Y) \leq 1$ where $D_o^*(X, Y) = \min\{\mu^* : Y/\mu^* \in T^*\}$.

Decomposition of TE under the metatechnology

Figure 2 shows a decomposition of TE under metatechnology. The metatechnology (T*) is constructed from two production technologies, T^{A} and T^{B}. The boundary of the metatechnology which indicates a metafrontier is represented by line *MM′*. Consider the production technology T^{A} where points A_1 and A_3 lie on the frontier *AA′* but point A_2 lies below the frontier *AA′*. TE_o^{A} of points A_1 and A_3 corresponding to its own frontier is equal to one whereas TE_o^{A} of point A_2 is equal to the ratio of $\mathrm{A}_2^*\mathrm{A}_2$ to $\mathrm{A}_2^*\mathrm{A}_2^{***}$. When the metafrontier (*MM′*) is considered, TE_o^* of point A_1 is still equal to one whereas TE_o^* of point A_2 is equal to the ratio of $\mathrm{A}_2^*\mathrm{A}_2$ to $\mathrm{A}_2^*\mathrm{A}_2^{**}$ and TE_o^* of the point A_3 is equal to the ratio of $\mathrm{A}_3^*\mathrm{A}_3$ to $\mathrm{A}_3^*\mathrm{A}_3^{**}$. Similarly, consider the production technology T^{B} where points B_1 and B_2 lie on the frontier *BB′* but point B_3 lies below the frontier *BB′*. TE_o^{B} of point B_1 and B_2 corresponding to its own frontier is equal to one whereas TE_o^{B} of points B_3 is equal to the ratio of $\mathrm{B}_3^*\mathrm{B}_3$ to $\mathrm{B}_3^*\mathrm{B}_3^{**}$. When the metafrontier (*MM′*) is considered, TE_o^* of points B_2 and B_3 is still the same as TE_o^{B} whereas TE_o^* of point B_1 is equal to the ratio of $\mathrm{B}_1^*\mathrm{B}_1$ to $\mathrm{B}_1^*\mathrm{B}_1^{**}$. When TE_{o} is measured relative to the group-specific technology and metatechnology, a

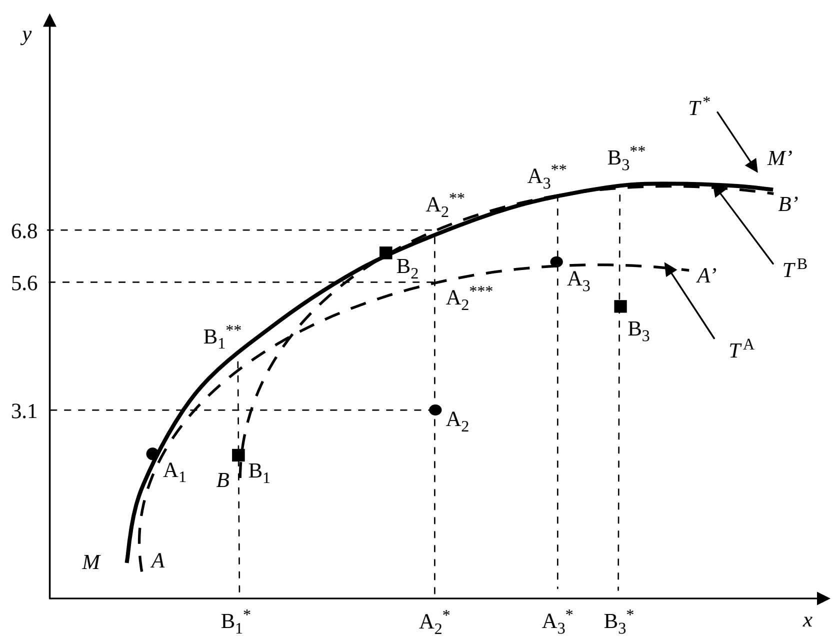

Figure 2. Decomposition of technical efficiency under the metafrontier.

gap can occur between the two technologies used as a reference. This gap is called a technology gap which is defined as the ratio of the distance function using observed data based on the metatechnology $T*$ to the group-specific technology T^k.

Using the output orientation, the technology gap ratio (*TGR*) can be defined as

$$TGR_o^k(X,Y) = \frac{D_o^*(X,Y)}{D_o^k(X,Y)} = \frac{TE_o^*(X,Y)}{TE_o^k(X,Y)}, \tag{4}$$

or it can be written as

$$TE_o^*(X,Y) = TE_o^k(X,Y) \times TGR_o^k(X,Y). \tag{5}$$

Equation (5) shows that TE measured with respect to the metatechnology ($T*$) can be decomposed into the product of the TE measured with respect to the k-th group technology (T^k) and the technology gap ratio. Note that the value of $TGR_o^k(X,Y)$ will be between zero and one so that $TE_o^*(X,Y) \leq TE_o^k(X,Y)$. For example, consider point A_2 in Figure 2: TE with respect to the frontier AA' can be measured by the ratio of the distances between $A_2^*A_2$ to $A_2^*A_2^{***}$. $TE_o^A(X_{A2}, Y_{A2}) = 3.1/5.6 = 0.554$, implying that 45% more of all outputs could possibly be produced from the given inputs by using frontier AA' as a reference. The TE with respect to the metafrontier (MM') can be measured by the ratio of the distances between $A_2^*A_2$ to $A_2^*A_2^{**}$. $TE_o^*(X_{A2}, Y_{A2}) = 3.1/6.8 = 0.456$, implying that 54% more of all outputs could possibly be produced from the given inputs by using the metafrontier (MM') as a reference. Therefore, $TGR_o^k(X,Y) = 0.456/0.554 = 0.823$, implying that the possible output for the frontier AA' is 82.3% of that represented by the metafrontier (MM').

Parametric approach to estimate the metafrontier function

The metafrontier function can be measured using the parametric approach of the SFA model. The metafrontier function using SFA constructs a smooth production technology by tangenting a specified functional form of production functions from each group-specific technology. It is a smooth function and not a segmented envelope of each group-specific technology[1].

When suitable panel data for each producer in each group during the time period, $t = 1, \ldots, T$ are available, the metafrontier estimation using the SFA can be achieved using a two-step procedure. First, the stochastic production frontier for each group is estimated and compared with that for all producers. Then, a statistical test is performed to examine whether all producers in different groups have potential access to the same technology.

If the group k consists of data on I^k producers, the stochastic production frontier model for the i-th producer at time period t based on the group-specific data and the pooled data is given as follows.

$$\ln Y_{it}^c = \ln f\left(X_{it}^c, t; \beta^c\right) + v_{it}^c - u_{it}^c, \tag{6}$$

where superscript c refers to a choice of the stochastic production frontier model (if $c = k$, Equation (6) refers to the stochastic group-specific production frontier model when the data for the i-th producer in the k-th group in the t-th time period are used, and if $c = p$, Equation (6) refers to the stochastic pooled production frontier model when the data for all producers in all groups in all time periods are used); Y_{it}^c denotes the output quantity for the i-th producer in the t-th time period; X_{it}^c denotes the input quantity for the

i-th producer in the t-th time period; β^cs are unknown parameters associated with the X-variables to be estimated; v_{it}^cs are a two-sided random-noise component assumed to be i.i.d. $N(0, \sigma_v^{2c})$ and u_{it}^cs are a non-negative technical inefficiency component. The v_{it}^c and u_{it}^c are distributed independently of each other and of the regressors. The non-negative technical inefficiency component, u_{it}^c, is assumed to follow a half normal distribution, $u_{it}^c \sim$ i.i.d $N^+(0, \sigma_u^{2c})$, and is defined by some appropriate inefficiency model (Battese and Coelli 1992)[2].

Following Battese and Coelli (1992), the stochastic group-specific and pooled production frontier models, taking the log-quadratic translog functional form under a non-neutral TC assumption, can be written as follows

$$\begin{aligned} \ln Y_{it}^c = \beta_0^c + \sum_{n=1}^{N} \beta_n^c \ln X_{nit}^c + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm}^c \ln X_{nit}^c \ln X_{mit}^c \\ + \sum_{n=1}^{N} \beta_{nt}^c \ln X_{nit}^c \cdot t + \beta_t^c t + \frac{1}{2}\beta_t^c t^2 + v_{it}^c - u_{it}^c, \end{aligned} \tag{7}$$

where $m, n = 1, \ldots, N$ index of input quantities and $u_{it}^c = \{\exp[-\eta(t-T)]\}u_i^c$ where ηs are parameters to be estimated and u_i^cs are non-negative random variables which are assumed to account for technical inefficiency in production and are assumed to be i.i.d. as truncations at zero of the $N^+(0, \sigma_u^{2c})$ distribution. Young's theorem requires that the symmetry restriction be imposed so that $\beta_{nm} = \beta_{mn}$ for all $m,n = 1,2,3$.

The output-orientated TE for the i-th producer in the t-th time period is given by

$$TE_{oit}^c = \exp\left\{-u_{it}^c\right\}. \tag{8}$$

If the stochastic frontiers across groups do not differ, then the stochastic pooled frontier function can be used as a grand technology[3]. However, if the stochastic frontiers across groups do differ, the metafrontier function will be used as a grand technology for each group. The second step will involve estimating the metafrontier function. The metafrontier function using SFA does not fall below the deterministic functions for the stochastic group-specific frontier model. In order to obtain estimated parameters of the metafrontier function, we need to ensure that the estimated function best envelops the deterministic components of the estimated stochastic frontiers for the different groups. Battese *et al.* (2004) proposed a method called the minimum sum of absolute deviations to identify the best envelope. The metafrontier function is estimated by solving the following LP problem.

$$\underset{\beta^*}{\mathrm{Min}} \sum_{i=1}^{I}\sum_{t=1}^{T} |(x_{it}\beta^* - x_{it}\hat{\beta}^k)| \equiv \bar{x}\beta^* \tag{9}$$

such that

$$x_{it}\beta^* \geq x_{it}\hat{\beta}^k,$$

where x_{it} is the logarithm form of the input quantity for the i-th producer in the t-th time period; $\bar{x}$ denotes the row vector mean of the elements of the x_{it} vector for all observations in the data set; $\hat{\beta}^k$s are the estimated coefficients obtained from the stochastic group-specific frontiers obtained from Equation (7) and β^*s are parameters of the metafrontier function to be estimated.

Once the β^* parameters of the metafrontier function in Equation (9) are estimated, the decomposition of TE under the metafrontier can be calculated. The technology gap for the *i*-th producer in the *k*-th group in the *t*-th time period can be obtained by

$$TGR_{oit}^{k}(X,Y) = \frac{e^{x_{it}\beta^k}}{e^{x_{it}\beta^*}}. \tag{10}$$

Then a measure of the output-oriented TE relative to the metafrontier, $TE_o^*(X,Y)$, can be obtained using Equation (5).

Data sources and descriptions

A balanced panel data set of 28 provinces covering the period 1991–2005 is used in the empirical analysis. Figure 3 illustrates the location of all provinces in China. Provinces selected for analysis include all provinces except Hainan and Tibet, owing to missing information[4]. Considering regional disparities, all provinces are ranked by using GDP per capita in 2001 according to the definition presented in Mao and Koo (1997). Provinces are divided into two groups of technologies: advanced-technology and low-technology provinces. Each group consists of 14 provinces. A list of the provinces in each group is included in Figure 3.

The primary data on agricultural production were extracted from the official data sources – *China Statistical Yearbook* and *Chinese Agricultural Statistical Yearbook*. These officially published data have been extensively used to evaluate efficiency and TFP (Fan 1991, Wu 1995, Mao and Koo 1997). The data used in this study comprise measurements of agricultural output and input quantities. The production technology is represented by one output and six inputs. The definitions of these variables are summarised as follows:

- **Dependent variable:** The gross output value of farming at 1990 constant prices in billions of yuan (y) is chosen as the dependent variable. The gross output value of farming aggregates physical output from seven grain crops and 12 commercial crops. However, it excludes the value of forestry, animal husbandry, handicraft products for self-consumption or for sale as a sideline occupation and the total value of industries run by villages and cooperative organisations under villages.

Advanced-Technology Provinces	*Low-Technology Provinces*
1. Beijing	1. Shanxi
2. Tianjin	2. Inner-Mongolia
3. Hebei	3. Anhui
4. Liaoning	4. Jiangxi
5. Jilin	5. Henan
6. Heilongjiang	6. Hunan
7. Shanghai	7. Guangxi
8. Jiangsu	8. Sichuan
9. Zhejiang	9. Guizhou
10. Fujian	10. Yunnan
11. Shandong	11. Shaanxi
12. Hubei	12. Gansu
13. Guangdong	13. Qinghai
14. Xinjiang	14. Ningxia

Figure 3. Location of advanced- and low-technology provinces.

- **Independent variables:** Following the existing literature, independent variables include six important physical inputs: capital, labour, chemical fertiliser, pesticide, plastic film and irrigation (Lin 1992, Wu 1995, Liu and Wang 2005).

Capital input (x_1) denotes farm machinery measured in millions of KW, mainly including big tractors and walking tractors. Other inputs such as draft animals are excluded in this study owing to the lack of information in the provincial statistics.

Labour force denotes the total number of rural workers directly engaged in production in agriculture, forestry, animal husbandry and fishery annually. To measure the labour input in the farming sector (x_2), we followed the calculation by Lin (1992) to weight the labour input in agriculture by the value of the share of farming output in total agricultural output.

Chemical fertiliser (x_3) refers to the pure-content quantity of chemical fertiliser applied in yearly agricultural production in tons. The pure-content gross quantity of chemical fertiliser is calculated to convert the gross weight into weight containing 100% of effective components.

Pesticide (x_4) is the quantity of chemical pesticides applied in agriculture, reported in tons annually.

Plastic film (x_5) includes that used for covering young plants and seeds, listed in tons annually.

Irrigation is a very important factor in Chinese agricultural production. An effectively irrigated area including not only the full set of technological irrigation facilities but also adequate water sources for normal agricultural irrigation can be used as an irrigation variable. The irrigation variable (x_6) used in this study is defined as the ratio of effectively irrigated area to total cultivated area. Total cultivated land area refers to land that is ploughed regularly for growing crops, excluding the land of tea plantations, orchards, nurseries of young plants, forest land, natural and man-made grassland.

Descriptive statistics of the variables used in the study summarised by the two groups of technology defined above are presented in Table 1.

Results

Parameter estimates and production structure

The data described in the previous section were used in the estimation of the stochastic group-specific and pooled production functions shown in Equation (7). The stochastic

Table 1. Descriptive statistics of variables, 1991–2005.

Variables	Unit	Advanced-technology provinces	Low-technology provinces	All provinces
Dependent variable				
Output	Billion yuan	27.678 (19.520)	22.505 (17.094)	25.092 (18.507)
Independent variables				
Capital	1000 kw	4615.148 (4453.458)	4160.390 (5604.301)	4387.769 (5060.772)
Labour	1000	4752.045 (3724.526)	7967.061 (5698.546)	6359.553 (5070.276)
Fertiliser	Million kg	1451.905 (1127.808)	1305.492 (1033.238)	1378.699 (1082.749)
Pesticide	Million kg	48.823 (40.953)	33.195 (31.282)	41.009 (37.228)
Plastic	Million kg	51.025 (52.847)	34.573 (28.218)	42.799 (43.106)
Irrigation	%	64.290 (24.070)	43.490 (18.510)	53.891 (23.837)

Notes: Means are calculated. Standard deviations are presented in parentheses.

group-specific production functions are estimated using the data for the advanced and low-technology provinces separately whereas the stochastic pooled production function is estimated using the data for all provinces. The data variables used in the model estimation were normalised by their respective geometric means. The estimated coefficients for each model are presented in Table 2. The estimation results from each model are similar and all first-order coefficients have the expected signs except for the estimated parameters β_{x4} of the low-technology provinces model.

The likelihood ratio (LR) test statistic for the null hypothesis that the group-specific frontiers are identical is 106.44. The LR test statistic follows a chi-square distribution with 39 degrees of freedom. The null hypothesis was rejected with a p-value less than 0.001. This result implies that the group-specific frontiers are not the same. Therefore, the metafrontier function presented in Equation (9) needs to be estimated. Table 2 also presents the estimated coefficients of the stochastic metafrontier function. All first-order coefficients have the expected signs and can also be interpreted as the production elasticities, evaluated at the sample means. The estimates of the input elasticities under the stochastic metafrontier function model are 0.0413, 0.2446, 0.4341, 0.0530, 0.0690 and 0.5285 for capital, labour, fertiliser, pesticide, plastic and irrigation respectively. The sum of the input elasticities provides information about scale economies and is 1.3705, indicating that the technology exhibits moderately increasing returns to scale at the sample mean. The first order coefficients of the time trend variable provide estimates of the average annual rate of TC. The stochastic metafrontier function model suggests that the technology is improving at a rate of 2.71% per annum.

Table 3 provides annual average production elasticities of inputs for 1991–2005. The production elasticity for capital decreases over the period by 7.42% per annum. The production elasticity for labour increases during 1991–93 and decreases during 1994–2005, leading to a decrease by 2.40% per anuum. The production elasticity for fertiliser decreases during 1991–2002 and increases during 2003–05, leading to an increase by 0.44% per annum. The production elasticities for pesticide and plastic increase throughout the period by 12.79% and 7.84% per annum respectively. The production elasticity for irrigation increases during 1991–2002 and decreases during 2003–05, leading to an increase by 2.11% per annum. The results indicate that the annual rates of increase of production elasticities for fertiliser, pesticide, plastic and irrigation are greater than the rates of decrease for capital and labour. The results also show that labour and fertiliser still make important contributions to output, and thus improving the quality of farmers and applying modern physical inputs is also crucial to TFP growth.

Discussion of TE decomposition under the metafrontier

Table 4 provides average TE scores relative to the stochastic group-specific frontier and metafrontier technologies as well as TGR scores for each group of provinces during 1991–2005. Moreover, Table A1 in the Appendix reports TE scores relative to the stochastic group-specific frontier and metafrontier technologies as well as TGR scores for all 28 provinces during 1991–2005. TE scores relative to the group-specific technology for the advanced-technology provinces range from 0.688 by Hebei to 0.978 by Guangdong with an average of 0.806. TE scores relative to the group-specific technology for the advanced-technology provinces were decreasing over time. Based on the metafrontier technology as a reference, TE scores for the advanced-technology provinces range from 0.661 by Hebei to 0.940 by Guangdong with an average of 0.764. The average TE score implies that the advanced-technology provinces in this study were, on average, producing

Table 2. Estimated parameters of stochastic group-specific frontier and metafrontier models.

	Stochastic frontier							
Parameters[a]	Advanced-technology provinces		Low-technology provinces		All provinces		Metafrontier[b]	
β_0	2.6686	(0.0465)	2.5797	(0.0537)	2.5495	(0.0433)	2.6293	(0.0150)
β_{x1}	0.0420	(0.0317)	0.0184	(0.0289)	0.0439	(0.0164)	0.0413	(0.0085)
β_{x2}	0.3646	(0.0614)	0.3304	(0.1202)	0.2947	(0.0356)	0.2446	(0.0060)
β_{x3}	0.2906	(0.0727)	0.5293	(0.1149)	0.3859	(0.0552)	0.4341	(0.0167)
β_{x4}	0.0051	(0.0519)	−0.0140	(0.0658)	0.0358	(0.0312)	0.0530	(0.0113)
β_{x5}	0.0678	(0.0392)	0.0255	(0.0309)	0.0203	(0.0177)	0.0690	(0.0064)
β_{x6}	0.5520	(0.1193)	0.8039	(0.2364)	0.4799	(0.0748)	0.5285	(0.0310)
β_t	0.0421	(0.0059)	0.0207	(0.0078)	0.0365	(0.0033)	0.0271	(0.0010)
β_{x11}	0.0211	(0.0355)	−0.0295	(0.0267)	−0.0067	(0.0204)	−0.0027	(0.0110)
β_{x12}	−0.2059	(0.0510)	0.0128	(0.0575)	−0.0776	(0.0274)	−0.1603	(0.0126)
β_{x13}	0.1199	(0.0520)	−0.0125	(0.0660)	0.0672	(0.0398)	0.0946	(0.0250)
β_{x14}	0.0374	(0.0442)	−0.0420	(0.0339)	−0.0314	(0.0228)	0.0230	(0.0123)
β_{x15}	0.0408	(0.0359)	0.0009	(0.0218)	0.0176	(0.0159)	0.0825	(0.0116)
β_{x16}	−0.1707	(0.0775)	0.1570	(0.1130)	−0.0315	(0.0663)	−0.2160	(0.0231)
β_{x22}	0.3070	(0.1112)	−0.2944	(0.2748)	0.1332	(0.0685)	0.0839	(0.0289)
β_{x23}	−0.0850	(0.1230)	0.1517	(0.3298)	−0.1045	(0.0962)	−0.1217	(0.0589)
β_{x24}	−0.1129	(0.0713)	0.0083	(0.1219)	−0.0074	(0.0420)	0.0834	(0.0308)
β_{x25}	−0.0272	(0.0570)	0.0230	(0.0633)	−0.0007	(0.0282)	0.0424	(0.0130)
β_{x26}	0.7263	(0.1500)	−0.5272	(0.4302)	0.6944	(0.1135)	0.5261	(0.0411)
β_{x33}	−0.1962	(0.2384)	−0.0540	(0.5815)	0.2132	(0.1840)	0.5670	(0.1326)
β_{x34}	0.1590	(0.0900)	0.0428	(0.1775)	−0.0047	(0.0648)	−0.2128	(0.0448)
β_{x35}	0.1951	(0.1022)	−0.1470	(0.1087)	−0.0728	(0.0577)	−0.1915	(0.0198)
β_{x36}	−0.4919	(0.2330)	1.0752	(0.6946)	−0.3362	(0.1899)	−0.3234	(0.0722)
β_{x44}	−0.0311	(0.0210)	−0.1430	(0.1051)	−0.0005	(0.0192)	0.0379	(0.0107)
β_{x45}	−0.0691	(0.0408)	0.0990	(0.0506)	0.0330	(0.0258)	0.0380	(0.0131)
β_{x46}	−0.0037	(0.1043)	0.1337	(0.3230)	−0.0659	(0.0922)	−0.0456	(0.0623)
β_{x55}	−0.1638	(0.0637)	−0.0084	(0.0264)	0.0120	(0.0194)	0.0029	(0.0064)
β_{x56}	0.0586	(0.0959)	−0.3459	(0.1728)	−0.1349	(0.0819)	−0.0458	(0.0607)
β_{x66}	0.4344	(0.5484)	−2.6276	(0.9912)	1.1428	(0.4167)	0.3150	(0.1620)

Table 2 – *continued*

Parameters[a]	Stochastic frontier: Advanced-technology provinces		Stochastic frontier: Low-technology provinces		Stochastic frontier: All provinces		Metafrontier[b]	
β_{x1t}	−0.0213	(0.0048)	0.0039	(0.0055)	−0.0050	(0.0027)	−0.0212	(0.0014)
β_{x2t}	0.0324	(0.0085)	−0.0061	(0.0149)	0.0164	(0.0047)	0.0007	(0.0028)
β_{x3t}	−0.0369	(0.0103)	0.0174	(0.0164)	−0.0185	(0.0071)	−0.0024	(0.0023)
β_{x4t}	0.0115	(0.0058)	−0.0033	(0.0100)	0.0074	(0.0038)	0.0109	(0.0031)
β_{x5t}	0.0093	(0.0047)	0.0005	(0.0065)	−0.0003	(0.0033)	0.0087	(0.0022)
β_{x6t}	0.0501	(0.0122)	−0.0318	(0.0369)	0.0546	(0.0106)	0.0448	(0.0057)
β_{tt}	0.0004	(0.0011)	0.0006	(0.0019)	0.0016	(0.0008)	0.0004	(0.0005)
σ^2	0.0146	(0.0019)	0.0122	(0.0016)	0.3107	(0.4543)		
γ	0.7200	(0.0633)	0.6612	(0.0568)	0.9830	(0.0249)		
η	−0.0075	(0.0120)	0.0136	(0.0089)	−0.0082	(0.0056)		
Log-likelihood	256.1712		235.9472		438.8973			

Note: Numbers in parentheses are standard errors.
[a] Subscripts on β_x coefficients refer to inputs: 1 = capital; 2 = labour; 3 = fertiliser; 4 = pesticide; 5 = plastic and 6 = irrigation.
[b] Standard deviations of the metafrontier estimates are calculated using parametric bootstrapping as presented in Battese *et al.* (2004).

Table 3. Annual average production elasticities for different inputs, 1991–2005.

	Capital	Labour	Fertiliser	Pesticide	Plastic	Irrigation
1991–93	0.081	0.297	0.434	0.029	0.053	0.471
1994–96	0.075	0.306	0.426	0.032	0.054	0.489
1997–99	0.054	0.299	0.412	0.053	0.071	0.537
2000–02	0.036	0.278	0.399	0.076	0.072	0.650
2003–05	0.029	0.215	0.453	0.101	0.114	0.589
1991–2005	**0.041**	**0.245**	**0.434**	**0.053**	**0.069**	**0.529**

80.6% of the outputs that could potentially be produced from the given inputs by using their own technologies as a reference and 76.4% using the metafrontier technology as a reference. The estimates of TGR for the advanced-technology provinces range from 0.847 by Shanghai to 0.980 by Heilongjiang with an average of 0.948. This result implies that the possible output for the advanced-technology provinces based on their group-specific technology is, on average, 94.8% of that represented by the metafrontier technology. Hebei and Tianjin are the two lowest ranked TE scores relative to both group-specific and metafrontier technologies whereas Guangdong and Liaoning are the two highest ranked TE scores relative to both technologies. The ranking of the TE scores from other provinces is not very different relative to the two technologies except for Shanghai. Shanghai is the third highest ranked TE score relative to its group-specific technology while it is the fifth lowest ranked TE score relative to the metafrontier technology.

Turning to the low-technology provinces, TE scores relative to their own technology range from 0.581 by Ningxia to 0.979 by Sichuan with an average of 0.732. TE scores relative to the group-specific technology for the low-technology provinces were increasing over time. Based on the metafrontier technology as a reference, TE scores for the low-technology provinces range from 0.443 by Ningxia to 0.842 by Inner Mongolia with an average of 0.644. The average TE score implies that the low-technology provinces in this study, on average, could potentially produce 27% more outputs from the given inputs by using their own technologies as a reference and 36% more outputs using the metafrontier technology as a reference. The estimates of TGR for the low-technology provinces range from 0.764 by Ningxia to 0.975 by Gansu with an average of 0.882. This result implies that the possible output for the low-technology provinces based on their group-specific technology is, on average, 88.2% of that represented by the metafrontier technology. Ningxia and Anhui have the two lowest ranked TE scores relative to the group-specific technology while Ningxia still has the lowest ranked TE score relative to the metafrontier technology and Anhui has the fourth lowest ranked TE score relative to the metafrontier technology. Sichuan and Inner Mongolia have the two highest ranked TE scores relative to both technologies. The ranking of the TE scores from other provinces is quite different relative to the two technologies.

The empirical findings show that the advanced-technology provinces had an average TE higher than the low-technology provinces. The advanced-technology provinces generally led in terms of TGR and had smaller variation of TGR than the low-technology provinces. The comparatively low TE scores in the low-technology provinces imply that the low-technology provinces were operating far from the metafrontier. The fluctuation of TE measured with respect to the metafrontier function indicates that it is possible that Chinese agricultural TFP growth can be improved through the improvement of TE.

Table 4. TE scores by group-specific and metafrontier technologies and TGR for each group, 1991–2005.

	Advanced-technology provinces			Low-technology provinces		
	TE^k	TGR	TE^*	TE^k	TGR	TE^*
1991	0.815 (0.075)	0.911 (0.055)	0.744 (0.096)	0.710 (0.142)	0.904 (0.113)	0.636 (0.115)
1992	0.814 (0.076)	0.916 (0.042)	0.746 (0.078)	0.714 (0.140)	0.907 (0.076)	0.645 (0.119)
1993	0.813 (0.076)	0.957 (0.042)	0.778 (0.078)	0.717 (0.139)	0.904 (0.073)	0.646 (0.126)
1994	0.811 (0.077)	0.966 (0.029)	0.784 (0.083)	0.720 (0.138)	0.909 (0.071)	0.653 (0.126)
1995	0.810 (0.077)	0.977 (0.022)	0.791 (0.079)	0.723 (0.136)	0.901 (0.066)	0.649 (0.116)
1996	0.809 (0.078)	0.979 (0.014)	0.792 (0.077)	0.726 (0.135)	0.899 (0.067)	0.651 (0.123)
1997	0.808 (0.078)	0.973 (0.036)	0.785 (0.077)	0.729 (0.133)	0.885 (0.072)	0.643 (0.113)
1998	0.806 (0.079)	0.946 (0.088)	0.761 (0.092)	0.732 (0.132)	0.871 (0.089)	0.636 (0.117)
1999	0.805 (0.079)	0.959 (0.055)	0.771 (0.084)	0.735 (0.131)	0.869 (0.098)	0.637 (0.122)
2000	0.804 (0.080)	0.963 (0.055)	0.773 (0.083)	0.738 (0.129)	0.817 (0.140)	0.599 (0.131)
2001	0.802 (0.080)	0.956 (0.053)	0.766 (0.074)	0.741 (0.128)	0.886 (0.079)	0.655 (0.123)
2002	0.801 (0.081)	0.936 (0.066)	0.749 (0.086)	0.743 (0.127)	0.881 (0.076)	0.656 (0.129)
2003	0.800 (0.081)	0.940 (0.064)	0.751 (0.089)	0.746 (0.125)	0.869 (0.087)	0.648 (0.124)
2004	0.799 (0.082)	0.925 (0.075)	0.739 (0.101)	0.749 (0.124)	0.869 (0.090)	0.650 (0.120)
2005	0.797 (0.082)	0.919 (0.080)	0.732 (0.102)	0.752 (0.123)	0.868 (0.098)	0.652 (0.124)
1991–2005	**0.806 (0.076)**	**0.948 (0.058)**	**0.764 (0.086)**	**0.732 (0.128)**	**0.883 (0.089)**	**0.644 (0.119)**

Decomposition of TFP change

TFP change (TFPC) is generally defined as the residual change in output not explained by the change in input use. TFPC can be measured and decomposed after the metafrontier function in Equation (9) is estimated. Figure 4 illustrates the TFPC decomposition under variable returns to scale (VRS) production technology. Using an output orientation, measures of the TEC, TE and SEC components in the TFPC are graphically illustrated in input–output space as follows. Let S_t and S_{t+1} be the technology under VRS in time periods t and $t+1$ respectively. Define T_t (T_{t+1}) as rays from the origin that are at a tangent to the production frontiers S_t (S_{t+1}). T_t and T_{t+1} represent the CRS technology, which shifts at the most productive scale size in time periods t and $t+1$ respectively. In periods t and $t+1$ the observed input–output combinations are located inside the production frontiers, implying that production is not technically efficient in either period. An output-orientated measure of TE defined in Farrell (1957) for the observation at time t, relative to the production frontier S_t, is given by the ratio ($\overline{0a}/\overline{0b}$), while the output orientated TE for the observation at time $t+1$, relative to the production frontier S_{t+1}, is given by the ratio ($\overline{0h}/\overline{0j}$). TEC, which measures the change in the output-orientated TE measure between periods t and $t+1$, is given by the ratio ($\overline{0h}/\overline{0j})/(\overline{0a}/\overline{0b}$). TC measures the movement of the production frontier from S_t to S_{t+1}. A measure of TC is defined as the geometric mean of the shift in S_t and S_{t+1} at input levels X_t and X_{t+1} and is given by the ratio $[(\overline{0h}/\overline{0d})/(\overline{0h}/\overline{0j}) \times (\overline{0a}/\overline{0b})/(\overline{0a}/\overline{0g})]^{1/2}$. The tangent points A and B in Figure 4 represent the maximum possible productivity or technically optimal scale of the production frontiers S_t and S_{t+1} respectively. In Figure 4 the firm is operating at a non-optimal scale in both periods. The firm may still be able to improve its productivity by exploiting scale economies. A measure of SEC represented by the change in output SE between periods t and $t+1$ data is given by the ratio ($\overline{0j}/\overline{0k})/(\overline{0b}/\overline{0c}$).

Following Orea (2002), a measure of TFPC for each firm between any two time periods can be calculated by using the estimates of the coefficients of the metafrontier and the firm-level sample data. The logarithmic form of the TFPC between periods t and $t+1$

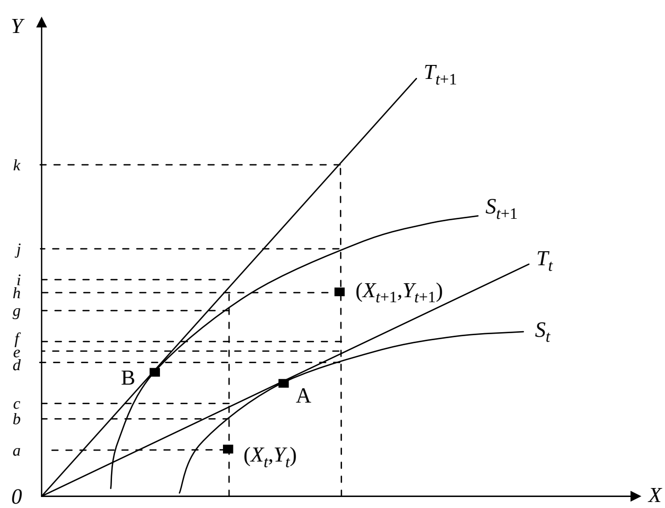

Figure 4. Output-orientated MPI decomposition under VRS production frontier.

for the *i*-th firm is defined as

$$\ln\left(\frac{TFP_{it+1}}{TFP_t}\right) = \ln\left(\frac{TE^*_{oit+1}}{TE^*_{oit}}\right) + \frac{1}{2}\left[\frac{\partial \ln f\left(X^*_{it+1}, t; \beta^*\right)}{\partial t} + \frac{\partial \ln f\left(X^*_{it}, t; \beta^*\right)}{\partial t}\right]$$
$$+ \frac{1}{2}\sum_{n=1}^{N}\left[\left(SF^*_{it+1}\cdot E^*_{nit+1}\right) + \left(SF^*_{it}\cdot E^*_{nit}\right)\right]\left(\frac{\ln X^*_{nit+1}}{\ln X^*_{nit}}\right), \qquad (11)$$

where the three terms on the right-hand-side of Equation (11) represent the output-oriented TEC, TC and SEC respectively.

The output-orientated TE measure, (TE^*_o), in Equation (11) is the output-orientated TE prediction of the *i*-th firm in the *t*-th time period, and is calculated from Equation (5). The TC measure, (TC_{itt+1}), is the mean of the TC measures evaluated at the period *t* and period $t+1$ data points. The SEC measure, (SEC_{itt+1}), relates to the change in scale efficiency, which requires calculation of the scale factor (*SF*) and input elasticity (E_n) evaluated at the period *t* and period $t+1$ data points. The *SF* of the *i*-th firm in the *t*-th time period $(SF^*_{it}) = (E^*_{it} - 1)/E^*_{it}$ where $E^*_{it} = \sum_{n=1}^{N} E^*_{nit}$ represents the scale elasticity and $E^*_{nit} = \partial \ln f(X^*_{it}, t; \beta^*)/\partial \ln X^*_{nit}$ is the production elasticity for the *n*-th input.

Discussion of TFPC decomposition

Table 5 presents weighted growth rates of decomposed TFPC by groups of provinces during 1991–2005. TFPC by all provinces increases by 62.45% over the sample period with a weighted average of about 3.234% per annum. TEC is almost negligible; it decreases by 0.43% over the sample period (average of about 0.029% per annum). SEC is less important; it increases by 1.46% over the sample period (average of 0.097% per annum). Overall, TC explains most of the TFPC. It increases by 60.79% with a weighted average of 3.166% per annum. The major findings show that TFPC in Chinese agriculture over the study period was mainly driven by technological progress. These aggregate figures obscure the diversity of effects across the two groups of provinces, although TC changes are dominant in both groups.

The advanced-technology provinces show TFPC of 65.6% over the sample period (average of about 3.362% per annum). TC increases by 66.3% (average of about 3.391% per annum) and the highest rate of technical progress is observed during 2000–02. TEC increases by 0.57% with a weighted average rise of about 0.038% per annum even though it was in decline after 1997. SEC decreases by 0.99% with a weighted average decrease of about 0.066% per annum although the entire decline is due to the negative SEC during 2000–2002. TC explains most of the TFPC throughout the period. There is impressive technical progress during 2000–02. TEC is a major influence on TFPC together with TC during 1991–96 and 2000–05. However, TEC is negligible relative to TC and SEC during 1997–99. SEC is negligible relative to TC and TEC throughout the period.

The low-technology provinces experience a TFP increase of 58.92% over the sample period (average of about 3.088% per annum). TC and SEC increase by 54.26% (average of about 2.890% per annum) and 4.57% (average of about 0.298% per annum). There is a major deterioration in SEC during 2000–02. TEC decreases slightly, by 1.48%, over the sample period with a weighted average decline of about 0.099% per annum. TC explains most of the TFPC for the entire period. There is impressive technical progress during

Table 5. Weighted annual growth rates of decomposed TFPC by province groups (%).

Period	TEC	TC	SEC	TFPC
Advanced-technology provinces				
1991–93	1.267	1.938	0.158	3.363
1994–96	1.100	3.612	0.003	4.714
1997–99	−0.283	3.829	−0.032	3.514
2000–02	−1.056	4.238	−0.667	2.515
2003–05	−0.840	3.338	0.206	2.703
1991–2005	**0.038**	**3.391**	**−0.066**	**3.362**
Low-technology provinces				
1991–93	−0.335	1.730	0.958	2.354
1994–96	0.512	2.957	0.901	4.371
1997–99	−0.853	3.215	0.463	2.825
2000–02	0.219	3.671	−1.419	2.471
2003–05	−0.041	2.875	0.587	3.420
1991–2005	**−0.099**	**2.890**	**0.298**	**3.088**
All provinces				
1991–93	0.529	1.842	0.525	2.897
1994–96	0.838	3.320	0.403	4.561
1997–99	−0.537	3.555	0.184	3.202
2000–02	−0.493	3.983	−1.005	2.484
2003–05	−0.480	3.132	0.377	3.028
1991–2005	**−0.029**	**3.166**	**0.097**	**3.234**

2000–02. TEC is negligible relative to TC and SEC throughout the period except in 1997–99. SEC is a major influence on TFPC together with TC during 2000–02.

Figure 5 presents the cumulative index plots of TFPC and its components for the advanced and low-technology provinces over the entire 1991–2005 period. The plot for the advanced-technology provinces shows that there was TFP progress over time and that it was mainly driven by TC. The advanced-technology provinces showed a decline in TFPC during 1991–93 and 2000–05 which resulted from a decline in TEC. There was a significant increase in TEC in 1993 and a major decrease in SEC in 2000. The plot for the advanced-technology provinces shows that TFPC was closely driven by TC throughout the period. TFPC and TC steadily improved while TEC and SEC remained stable, leading to an increase in TFPC over the entire period. Overall, TC explains most of the TFPC. However, TEC contributed more to TFPC than SEC throughout the period.

The plot for the low-technology provinces again shows that TFPC was closely driven by TC. TFPC steadily improved throughout the period except in 2000, when a decrease in TEC led to a decrease in TFPC. TC change steadily improved throughout the period. TEC remained stable and showed a small decrease during 1999–2000. SEC was stable and showed an increase during 1993–99. Overall, TC explains most of the TFPC and SEC contributed more to TFPC than TEC throughout the period.

The proportional growth of the average TEC, TC and SEC components constituting the average TFPC for all provinces in each group over the period 1992–2002 are also reported in Table A1 in the Appendix. All the provinces can be divided into different categories according to their TFPC and what sources contributed to their TFPC. All advanced-technology provinces except Heilongjiang showed TFP progress over the period. TFP decline in Heilongjiang was driven by decline in TC and SEC. Hebei is the only province in which TFP progress was driven by an increase in TEC, TC and SEC. TFP progress in Beijing, Zhejiang, Fujian and Guangdong was driven by an increase in TEC

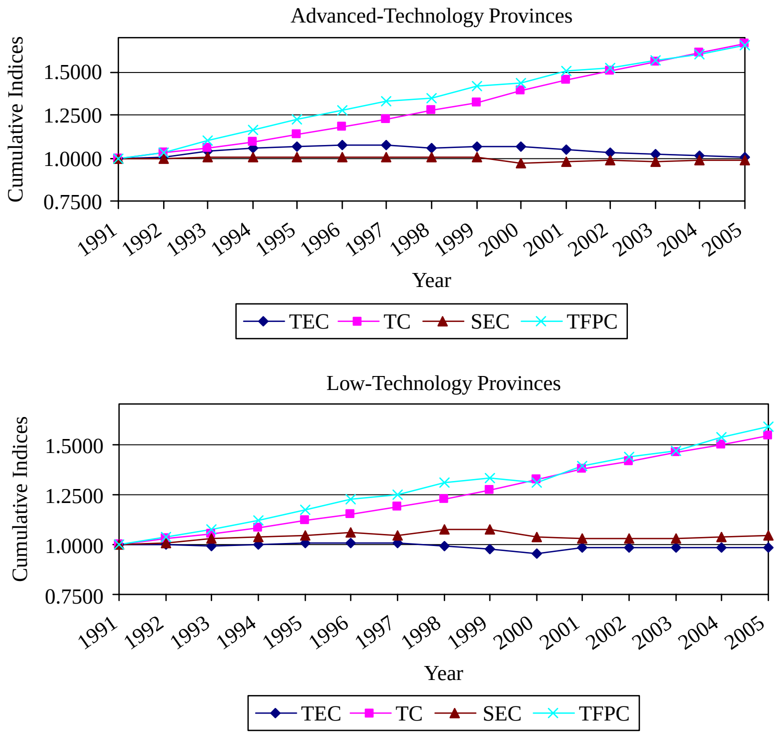

Figure 5. Cumulative indices of TEC, TC, SEC and TFPC by groups of provinces, 1991–2005.

and TC with a decrease in SEC. TFP progress in Tianjin, Shanghai, Jiangsu and Hubei was mainly attributable to technical progress, with a decline in TEC and SEC. Liaoning, Jilin, Shandong and Xinjiang showed an increase in the TC and SEC but a decrease in the TEC contribution to their TFP progress.

Similarly, all low-technology provinces except Inner Mongolia displayed TFP progress over the period. TFP decline in Inner Mongolia was driven by a decline in TEC and TC. TFP progress in all provinces except Qinghai and Ningxia was mainly driven by technical progress. Shanxi, Henan, Guizhou, Yunnan, Shaanxi and Gansu showed an increase in the contribution of TEC, TC and SEC to their TFP progress. TFP progress in Anhui and Guangxi was driven by an increase in TC and SEC but a decrease in TEC. TFP progress in Jiangxi, Hunan and Sichuan was mainly attributable to technical progress, with a decline in TEC and SEC.

Conclusions

With nearly one quarter of the potential agricultural resources and one-fifth of the world's population, China has the potential to supply a substantial share of the expected growth in food demand forecast for the first half of this century. This study utilises a parametric metafrontier function approach to measure and decompose Chinese agricultural TE and productivity by including all producers in different groups operating under their own technologies. Data on 28 provinces over the period 1991–2005 are used and the provinces are categorised into advanced and low-technology provinces on the basis of distinctive levels of economic development and production technologies.

The empirical findings indicate that the weighted average TFP in Chinese agriculture over the study period grew at 3.234% per annum, which was driven primarily by a 3.166% increase in TC. SEC exhibited a positive effect on TFPC whereas TEC was positive in early years but negative from 1997. TC was the major contributor to TFPC in both advanced and low-technology provinces. SEC and TEC exhibited negative effects on TFPC in the advanced and low-technology provinces respectively. Most of the advanced-technology provinces exhibited higher TE than the low-technology provinces. The comparatively low TE scores in low-technology provinces were found to be related to the TE measured with respect to its own-group technology and the technology gap ratio. As researchers and policy makers discuss the pros and cons of China's WTO commitments in agriculture, the analysis in this study suggests that there may benefit through the improvement of TE. The empirical results also show that labour and fertiliser still make important contributions to output, so that improving the skills of farmers and applying modern physical inputs is also crucial to TFPC.

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Notes

1. The metafrontier function can also be measured using DEA. The metafrontier function using DEA constructs a piece-wise linear convex production technology by enveloping all observed data from each group-specific technology. It is constructed without specifying a functional form for each group-specific technology and is a segmented envelope of each group-specific technology.
2. We follow the suggestion of Battese and Corra (1977) and replace the two variance parameters with the two new parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$.
3. The likelihood ratio (LR) test statistic is used to test the hypothesis that the group-specific frontiers are identical.
4. Chongqing is added together with Sichuan owing to the unavailability of separate data before 1998.

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Appendix

Table A1. Average TE, TGR and the TFP decomposition by province.

Provinces	TE^k	TGR	TE*	TEC	TC	SEC	TFPC
Advanced-technology provinces	(in percentage)						
Beijing	0.820	0.948	0.778	0.180	4.190	−0.173	4.197
Tianjin	0.740	0.938	0.694	−0.286	3.693	−0.024	3.384
Hebei	0.688	0.960	0.661	0.499	2.049	0.534	3.082
Liaoning	0.948	0.948	0.898	−0.239	3.076	0.143	2.979
Jilin	0.784	0.969	0.760	−0.392	0.705	0.325	0.638
Heilongjiang	0.839	0.980	0.822	0.012	−0.410	−0.344	−0.741
Shanghai	0.840	0.847	0.712	−2.439	6.957	−0.034	4.484
Jiangsu	0.793	0.960	0.761	−0.221	3.636	−0.088	3.327
Zhejiang	0.742	0.958	0.710	0.909	4.974	−0.914	4.969
Fujian	0.771	0.943	0.728	0.708	5.556	−0.257	6.007
Shandong	0.797	0.951	0.758	−0.198	3.559	0.225	3.585
Hubei	0.742	0.950	0.705	−0.037	4.486	−0.067	4.382
Guangdong	0.978	0.962	0.940	0.613	4.662	−0.786	4.489
Xijiang	0.806	0.958	0.772	−0.715	2.788	0.359	2.431
Average	**0.806**	**0.948**	**0.764**	**−0.115**	**3.566**	**−0.079**	**3.372**
Low-technology provinces							
Shanxi	0.615	0.903	0.554	0.277	1.188	0.534	2.000
Inner Mongolia	0.976	0.863	0.842	−1.092	−0.602	1.285	−0.408
Anhui	0.596	0.938	0.558	−0.306	2.435	0.446	2.575
Jiangxi	0.694	0.844	0.584	−1.698	6.440	−0.770	3.972
Henan	0.726	0.858	0.623	0.743	1.378	0.934	3.054
Hunan	0.699	0.789	0.551	−0.895	6.074	−0.724	4.455
Guangxi	0.720	0.934	0.672	−0.588	2.393	0.547	2.351
Sichuan	0.980	0.842	0.825	−0.184	4.642	−0.683	3.774
Guizhou	0.731	0.888	0.650	0.577	3.082	0.043	3.702
Yunnan	0.711	0.941	0.669	0.214	2.231	0.942	3.387
Shaanxi	0.649	0.966	0.627	0.549	0.668	1.160	2.378
Gansu	0.649	0.975	0.633	0.135	0.977	1.401	2.512
Qinghai	0.917	0.851	0.781	3.423	−1.893	0.449	1.980
Ningxia	0.581	0.764	0.443	1.048	−0.692	1.167	1.523
Average	**0.732**	**0.883**	**0.644**	**0.157**	**2.023**	**0.481**	**2.661**