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Productivity Growth, Technology Progress, and Efficiency Change in Chinese Agricultural Production From 1984 to 1993

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Abstract

This study applies a Data Envelopment Analysis (DEA) approach to analyze total factor productivity, technology, and efficiency changes in Chinese agricultural production from 1984 to 1993. Twenty-nine provinces in China were classified into advanced-technology and low-technology categories. The Malmquist productivity measures were decomposed into two components: technical change index and efficiency change index. The results showed that total factor productivity has risen in most provinces for both technology categories. Technical progress has been the most important factor to Chinese agricultural productivity growth since 1984 and will remain crucial to productivity growth in low-technology provinces. Low efficiency in many important agricultural provinces indicates a great potential for China to increase productivity through improving technical efficiency. Continuously expanding market economy and enhancing rural education may also help farmers to improve technical efficiency and productivity in agricultural production.

Keywords: Chinese agriculture, Total Factor Productivity (TFP), technology, technical efficiency, Data Envelopment Analysis (DEA).

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Keywords: Chinese agriculture, Total Factor Productivity (TFP), technology, technical efficiency, Data Envelopment Analysis (DEA).

Highlights

Rapid economic growth in China has significantly increased demand for agricultural commodities over the last decade. Economic reforms in rural areas were attributed most to Chinese agricultural production growth in early 1980s, while technological changes only accounted for a small proportion of this growth.

This study applied a nonparametric programming method to analyze productivity growth in the Chinese agricultural sector from 1984 to 1993. The total twenty-nine provinces in China were classified into advanced-technology and low-technology categories. With Data Envelopment Analysis (DEA), the Malmquist productivity measures were decomposed into two mutually exclusive components: technical change index and efficiency change index. This decomposition allowed us to identify the contributions of technical progress and improvement in technical efficiency to Chinese agricultural productivity growth.

DEA was used to calculate the component distance functions of the Malmquist index and to construct the best-practice (efficient) frontiers for both agricultural technology categories. The technical change and efficiency change indexes were obtained by comparing each province to the best-practice frontier with the same production technology. The Malmquist productivity index was calculated as a product of these two indexes.

Among the total 29 provinces in China, 26 provinces experienced agricultural productivity growth during the 1984-93 period, most of which was due to improved technological progress in agricultural production. Efficiency changes made little contribution to Chinese agricultural productivity growth. Advanced-technology provinces had higher average productivity and technology growths than had low-technology provinces in agricultural production. However, the average decline in technical efficiency in advanced-technology provinces was greater than that in low-technology provinces.

The results from this study indicates that technical changes were the most important factor to Chinese agricultural productivity growth in the post institutional reform era. Enhancing agricultural research and development and rural education to stimulate technical progress will be crucial to Chinese agricultural productivity growth, especially for the provinces with low-technology. Poor performance in technical efficiency in many important agricultural provinces indicate a great potential for China to increase agricultural productivity through improving technical efficiency. Continuously expanding market economy and enhancing rural education may also help farmers to adopt new technology to improve technical efficiency and productivity.

Productivity Growth, Technology Progress, and Efficiency Change in Chinese Agricultural Production From 1984 to 1993

Weining Mao and Won W. Koo*

Introduction

The Chinese economy has rapidly expanded and gradually moved to a market economy over the last decade. Economic expansion has doubled China's per capita income and increased Chinese food consumption. To meet the rapid increase in demand for agricultural products, the Chinese government has made tremendous efforts to increase its agricultural output through economic reforms, increasing government capital investment in the agricultural sector, increasing inputs in production, adopting new technology, and introducing improved seed varieties.

Economic reforms in rural areas stimulated farmers to increase agricultural output and to improve efficiency of resource allocation in agricultural production. Many studies showed that institutional changes accounted for most contributions to the increase in Total Factor Productivity (TFP) of Chinese agriculture. The rises in output prices and increases in the uses of inputs also contributed to the growth in agricultural output. However, technical changes contributed little to Chinese agricultural production growth in early 1980s.

In this study, we applied a recently developed technique to analyze productivity growth in agricultural sectors of 29 provinces in China from 1984 to 1993. The productivity increase in Chinese agriculture was decomposed into technical change and efficiency change using Data Envelopment Analysis (DEA). This technique allows us to isolate the contributions of improving efficiency from the contribution of technology progress.

The rest of this paper is organized as follows: the next section presents a review of previous studies on Chinese agricultural productivity and efficiency. The third section discusses productivity, economic efficiency, and their measurements. The fourth section outlines the Malmquist productivity indexes. The DEA approach to measuring Chinese agricultural efficiency and productivity is presented in the fifth section. The sixth section describes the data and their sources. The results and their implications for Chinese agriculture are discussed in the seventh section. A summary and conclusions are included in the last section.

Review of Literature on Chinese Agricultural Productivity and Efficiency

Since Chinese economic reforms spread out in rural areas in 1984, the impacts of these reforms on Chinese agricultural productivity have become of considerable interest to many economists. McMillan, Whalley, and Zhu (1989) used a Denison-Solow-type growth-accounting technique to analyze the impact of China's economic reforms on agricultural productivity growth. They decomposed the growth in TFP into a price component and an

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incentive component. They argued that price increases and strengthened individual incentives due to the introduction of the Household-Responsibility System (HRS) for post-1978 had mainly contributed to the increase in China's agricultural productivity.

Fan (1991) used an accounting approach to separate the relative contribution of institutional change, technological progress, and increases in inputs to the rapid Chinese agricultural production growth in the early 1980s. He found that about 63 percent of total productivity growth was attributed to efficiency improvement (institutional change) and 37 percent to technological change. Increases in inputs played an important role to Chinese agricultural growth. Total input growth accounted for about 57.7 percent of total production growth. However, technological change only accounted for 15.7 percent of total production growth in China, indicating that the potential of production growth can be achieved by stimulating technological progress in Chinese agriculture.

Lin (1992) used province-level panel data to evaluate the contribution of rural reforms on China's agricultural growth in the reform period. He estimated a Cobb-Douglas agricultural production function with four conventional inputs: land, labor, capital, and chemical fertilizers. In addition, six other variables were incorporated into the model to assess the impacts of farming institutional change, price adjustments, market reforms, and technological changes to agricultural productivity. He found that decollectivization had improved China's TFP and accounted for about half of the output growth during the 1978-1984 period. The adjustment of state procurement prices was also found to increase agricultural output. However, the effect of other market-related reforms on productivity and output growth was very small.

Fleisher and Liu (1992) used a Cobb-Douglas production function for agricultural output with a farm household survey data to test the hypotheses on economies of scale, diseconomies of multiple plots and multiple crops, and estimated their impacts on total productivity and the marginal products of labor and other inputs. They found that plot and crop consolidation within households could considerably increase China's agricultural productivity.

Gaynor and Putterman (1993) employed production team-level data to examine the effects of land decollectivization during the Chinese economic reforms of the 1980s. They found that agricultural output was concave in the proportion of land distributed according to work force as opposed to household size under a household decision-making model. Grain output also displayed the expected concave relationship with the land distribution parameter in a quadratic specification of the model.

Wen (1993) examined the performance of the successive rural institutions in China in terms of changes in the Total Factor Productivity Index (TFPI). He found that the HRS led to a considerable efficiency improvement and showed a clear advantage over the commune system in increasing the TFPI. The results of this study also showed that in more than 20 years, the commune system raised land productivity, but lowered labor productivity, and that HRS raised both land and labor productivity in Chinese agricultural production.

Travers and Ma (1994) used a variable elasticity model of the aggregate agricultural production function to analyze agricultural productivity and rural poverty in China. They argued that under current technologies and prices, increased agricultural production and farmer incomes could be achieved through further intensification of machinery and fertilizer use. They also argued that further irrigation development under the national poverty alleviation program could not lead to increased farmer incomes in China's poorest areas unless part of the capital costs are covered by government transfers.

Putterman and Chiacu (1994) reviewed factor weighted assumptions used in four studies of trends in TFP in Chinese agriculture and the factor elasticities estimated in 12 Chinese agricultural production function studies. They found that estimates of the output elasticities of land typically exceeded the upper bound weight for land used in the TFP studies. They also showed the sensitivity of TFP trends to factor assumptions by indicating that adopting average elasticities as factor weights leads to a less negative assessment of TFP performance during the collective period.

Wang, Wailes, and Cramer (1996) developed a shadow-price profit frontier model to examine production efficiency of Chinese agricultural households. They found that farmer's resource endowment and education are very important factors to influence Chinese farmers' allocative efficiency. Larger farm size (scale) and family size, higher per capita net income, and education increase profit efficiency. Both technical and allocative efficiencies can be improved by reducing market distortions. They suggested that Chinese agricultural productivity can be increased by continuously improving efficiency.

Most studies on Chinese agricultural productivity (McMillan et al., Lin, Fleisher and Liu, Gaynor and Putterman, Travers and Ma) used traditional parametric approaches to calculate TFP by estimating aggregate production functions. However, this approach has been criticized by many economists because of its aggregate assumptions, limitation of chosen functional forms, and divergent estimates of productivity (Arnade, 1994). Wen (1993) calculated the TFPI for the Chinese agricultural sector based on input factor weighted assumptions. But Putterman and Chiacu (1994) found that the output elasticities of land typically exceeded the upper bound weight for the factor used in the Chinese TFP studies.

No study has used a nonparametric approach such as DEA to analyze productivity growth in the Chinese agricultural sector, especially at the province level. In this study, we examined the performances of each province's agricultural production in terms of productivity growth, technical efficiency, and technical change from 1984 to 1993. The decomposition of productivity index allows us to identify the contributions of improved efficiency and technical progress to Chinese agricultural productivity growth.

Productivity, Production Efficiency, and Their Measurements

Productivity is used to measure rate of technical change in production (Chambers, 1988). Productivity can be conceptualized as two main components: partial factor productivity and total productivity. Partial factor productivity, also called average product, is defined as a ratio of output to a specific input. Let Y be denoted as output and x_i as any individual input factor, then partial productivity of input x_i (AP_i) is

$$AP_i = Y / x_i . \tag{1}$$

Partial factor productivity only measures the contribution of one particular input to technical change, ignoring the effects from other input factors.

TFP is defined as the average product of all input factors. It is the ratio of output to an index of inputs. Let X denote the index of all inputs, then TFP is

$$TFP = Y / X = Y / \sum \alpha_i x_i , \tag{2}$$

where α_i is the weight of input x_i.

TFP can be calculated by estimating aggregate production functions or cost functions with limited functional forms and imposed restrictions on econometric parameters. TFP can also be measured using indexes, such as Laspeyres, Paasche, Fisher, or Tornqvist-Theil indexes. Index approach imposes restrictions on production technology by putting weights on inputs and output.

Two types of production efficiency were defined by Farrell (1957): technical efficiency and allocative efficiency. Technical efficiency evaluates a firm's ability to obtain the maximum possible output from a given set of inputs, while allocative efficiency measures a firm's ability to maximize its profits by comparing the marginal revenue of product with the marginal costs of inputs. Traditionally, the stochastic production frontier approach was used to measure technical efficiency and allocative efficiency, given the technology and prices. However, this econometric approach requires the specification of production technology. Recently, a mathematical programming approach such as DEA was developed to measure technical efficiency by comparing the individual firm's production to the best-practice frontier (Seiford and Thrall, 1990).

This study applied the generalized Malmquist index, developed by Färe et al. (1994), to measure the contributions from the progress in technology and improvement in technical efficiency to the growth of productivity in Chinese agricultural production. The Malmquist index is constructed using the DEA approach.

The Malmquist Productivity Indexes

The Malmquist productivity indexes were proposed by Caves et al. (1982a, b) based on distance functions developed by Malmquist (1953). Färe et al. (1994) decomposed productivity growth into two mutually exclusive components: technical change and efficiency change over time. They calculated productivity change as the geometric mean of two Malmquist productivity indexes using output distance functions.

Let the production technology S^t for each time period t = 1, ..., T denotes the transformation of inputs, $x^t \in R^N_+$, into outputs, $y^t \in R^M_+$,

$$(3) \qquad S^t = \{(x^t, y^t): x^t \text{ can produce } y^t\},$$

where S^t is assumed to satisfy the required axioms to define meaningful output distance functions (Färe,1988).

Following Färe et al. (1994), the output distance function in time period t is defined as

$$(4) \qquad \begin{aligned} D_0^t(x^t, y^t) &= \inf\left[\theta: (x^t, y^t/\theta) \in S^t\right] \\ &= \left\{\sup\left[\theta: (x^t, \theta y^t) \in S^t\right]\right\}^{-1}. \end{aligned}$$

Distance function is defined as the inverse of the maximal proportional increase of the output vector y^t, given inputs x^t. It is also equivalent to the reciprocal of Farrell's (1957) measure of output efficiency, which measures TFP "catching-up" of an observation (a province in this study) to the best-practice frontier of technology. In this study, the best-practice frontier is the highest productivity observed in 29 provinces of China.

$D_0^t(x^t, y^t) = 1$ if and only if (x^t, y^t) is on the boundary or frontier of technology and production is technically efficient. If $D_0^t(x^t, y^t) < 1$, production at t is interior to the frontier of technology at t, and (x^t, y^t) is not technically efficient. The distance function measures the degree of technical inefficiency. The output distance function in time period t +1, $D_1^{t+1}(x^{t+1}, y^{t+1})$, can be defined as (4) with t replaced by t + 1.

Define output distance functions with respect to two different time periods as

(5) $$D_0^t(x^{t+1}, y^{t+1}) = \inf\left\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^t\right\}.$$

This is one mixed index that measures the maximal proportional change in outputs y^{t+1} given inputs x^{t+1}, under the technology at time period t. Similarly, we define the mixed distance function, $D_1^{t+1}(x^t, y^t)$, which measures the maximal proportional change in output y^t given inputs x^t, with respect to the technology at time period t +1.

Following Caves et al. (1982a), the Malmquist productivity index is defined as

(6) $$M_0^t = \frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}.$$

This ratio index measures the productivity changes originating from changes in technical efficiency at time period t and time period t + 1 under the technology in time period t. The technical efficiency changes from time period *t* to time period t + 1 can also be measured under the technology in time period t + 1. This Malmquist index is defined as

(7) $$M_1^{t+1} = \frac{D_1^{t+1}(x^{t+1}, y^{t+1})}{D_1^{t+1}(x^t, y^t)}.$$

Färe et al. (1994) specified the output-based Malmquist productivity change index as the geometric mean of (6) and (7) and decomposed it into two parts:

(8) $$\begin{aligned} M_0(x^{t+1}, y^{t+1}, x^t, y^t) &= \left\{\left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\right]\left[\frac{D_1^{t+1}(x^{t+1}, y^{t+1})}{D_1^{t+1}(x^t, y^t)}\right]\right\}^{1/2} \\ &= \frac{D_1^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}\left\{\left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_1^{t+1}(x^{t+1}, y^{t+1})}\right]\left[\frac{D_0^t(x^t, y^t)}{D_1^{t+1}(x^t, y^t)}\right]\right\}^{1/2} \\ &= E(x^{t+1}, y^{t+1}, x^t, y^t)\, T(x^{t+1}, y^{t+1}, x^t, y^t), \end{aligned}$$

where

$$E(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_1^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)}, \tag{9}$$

$$T(x^{t+1}, y^{t+1}, x^t, y^t) = \left\{ \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_1^{t+1}(x^{t+1}, y^{t+1})} \right] \left[\frac{D_0^t(x^t, y^t)}{D_1^{t+1}(x^t, y^t)} \right] \right\}^{1/2} .$$

E(·) is the relative efficiency change index under the constant returns to scale which measures the degree of catching up to the best-practice frontier for each observation between time period t and time period t + 1, while T(·) represents the technical change index which measures the shift in the frontier of technology (or innovation) between two time periods evaluated at x^t and x^{t+1}.

The decomposition of the Malmquist productivity index allows us to identify the contributions of catching up in efficiency and innovation in technlogy to the TFP growth. According to Färe et al. (1994), Malmquist indexes greater than one indicate growth in productivity. Malmquist indexes less than one indicate decline in productivity. In addition, improvments in any of the two components of the Malmquist productivity index are also associated with values greater than one, and declines are associated with values less than one.

Data Envelopment Analysis (DEA)

Färe et al. (1994) listed several traditional methods to calculate the Malmquist productivity index. But most of them require specification of a function form for technology. Charnes et al. (1978) proposed the DEA approach to construct a best-practice frontier without specifying production technology. Unlike traditional analysis techniques that look for the average path through the middle points of a series of data, DEA looks directly for a best-practice frontier within the data. Using a nonparametric linear programming technique, DEA takes account of all the inputs and outputs as well as differences in technology, capacity, competition, and demographics and then compares individuals with the best-practice (efficiency) frontier.

Färe et al. (1994) computed the Malmquist productivity indexes for a sample of 17 OECD countries using nonparametric programming approaches. They calculated the component distance functions of the Malmquist indexes through maximization of feasible outputs for the given inputs. Arnade (1994) also used the DEA method to calculate the Malmquist productivity indexes for the agricultural sectors of 77 countries from 1961 to 1987. Instead of using output distance functions, Arnade constructed the Malmquist indexes using input distance functions which minimize the input requirements for given outputs.

In this study, we used the DEA approach outlined by Färe et al. (1994) to construct the best-practice frontier at each time period for each technology category. Comparing each province to the best-practice frontier gives a measure of its catching up in efficiency to that frontier and a measure of shift in the frontier (or innovation in technology). Then, the Malmquist indexes, which measure the changes in TFP, are calculated as a product of these two components.

Assume that there are k = 1, ..., K provinces that produce m = 1, ..., M outputs $y^t_{k,m}$ using n = 1, .., N inputs $x^t_{k,n}$ at each time period t = 1, ..., T. Under DEA, the reference technology with constant returns to scale at each time period t from the data can be defined as

$$
(10) \qquad \begin{aligned}
G^t = [\,(x^t,\ y^t):\ y^t_m \le \sum_{k=1}^{K} z^t_k y^t_{k,m} \qquad & m = 1,\ldots,M,\\
\sum_{k=1}^{K} z^t_k x^t_{k,n} \le x^t_n \qquad & n = 1,\ldots,N,\\
z^t_k \ge 0 \qquad & k = 1,\ldots,K\ ],
\end{aligned}
$$

where z^t_k refers weight on each specific cross-sectional observation. Following Afriat (1972), the assumption of constant returns to scale may be relaxed to allow variable returns to scales by adding the following restriction:

$$
(11) \qquad \sum_{k=1}^{K} z^t_k = 1 \qquad (\text{VRS}).
$$

Following Färe et al. (1994), we use an enhanced decomposition of the Malmquist index to analyze the productivity growth in agricultural production of 29 provinces in China. We decompose the efficiency-change component calculated relative to the constant-returns-to-scale technology into a pure efficiency-change component (calculated relative to the variable-returns-to-scale technology) and a scale-change component which captures changes in the deviation between the variable-returns and constant-returns-to-scale technology.

To construct the Malmquist productivity index of province k' between t and t + 1, we use the DEA approach to calculate the following four distance functions: $D^t_0(x^t, y^t)$, $D^{t+1}_1(x^t, y^t)$, $D^t_0(x^{t+1}, y^{t+1})$, and $D^{t+1}_1(x^{t+1}, y^{t+1})$. These distance functions are the reciprocals of the output-based Farrell's measure of technical efficiency. The nonparametric programming models used to calculate the output-based Farrell measure of technical efficiency for each province k’ = 1, ..., K, is expressed as

$$\text{(12)} \qquad \left[D_0^t(x_{k'}^t,\ y_{k'}^t) \right]^{-1} = \max\ \lambda^{k'}$$

subject to

$$\text{(13)} \qquad \begin{aligned} &\lambda^{k'} y_{k',m}^t \le \sum_{k=1}^{K} z_k^t y_{k,m}^t && m = 1,\dots,M, \\ &\sum_{k=1}^{K} z_k^t x_{k,n}^t \le x_{k',n}^t && n = 1,\dots,N, \\ &\sum_{k=1}^{K} z_k^t = 1, && (\text{VRS}) \\ &z_k^t \ge 0 && k = 1,\dots,K\ ]. \end{aligned}$$

The computation of $D_1^{t+1}(x^{t+1}, y^{t+1})$ is similar to (13), where t + 1 is substituted for t.

Construction of the Malmquist index also requires calculation of two mixed-distance functions, which is computed by comparing observations in one time period with the best-practice frontier of another time period. The inverse of the mixed-distance function for observation k’ can be obtained from

$$\text{(14)} \qquad \left[D_0^t(x_{k'}^{t+1},\ y_{k'}^{t+1}) \right]^{-1} = \max\ \lambda^{k'}$$

subject to

$$\text{(15)} \qquad \begin{aligned} &\lambda^{k'} y_{k',m}^{t+1} \le \sum_{k=1}^{K} z_k^t y_{k,m}^t && m = 1,\dots,M, \\ &\sum_{k=1}^{K} z_k^t x_{k,n}^t \le x_{k',n}^{t+1} && n = 1,\dots,N, \\ &\sum_{k=1}^{K} z_k^t = 1 && (\text{VRS}), \\ &z_k^t \ge 0 && k = 1,\dots,K\ ]. \end{aligned}$$

To measure changes in scale efficiency, the inverse output distance functions under the variable-returns-to-scale technology are also calculated by adding (11) into the constraints in (13) and (15). Technical change (TECHCH) is calculated relative to the constant-returns-to-scale technology. Scale efficiency change (SCH) in each time period is constructed as the ratio of the distance function satisfying constant returns to scale to the distance function under variable returns to scale, while the pure efficiency change (PEFFCH) is defined as the ratio of the own-period distance functions in each period under variable returns to scale. With these two distance functions with respect to the variable-returns-to-scale technology, the decomposition of (8) becomes

$$
\begin{aligned}
M_0(x^{t+1}, y^{t+1}, x^t, y^t) &= T(x^{t+1}, y^{t+1}, x^t, y^t) \times E(x^{t+1}, y^{t+1}, x^t, y^t) \\
&= \text{TECHCH} \times \text{EFFCH} \\
&= \text{TECHCH} \times \text{PEFFCH} \times \text{SCH},
\end{aligned} \tag{16}
$$

in advanced-technology provinces where EFFCH denotes the efficiency change calculated under constant returns to scale.

Data Sources and Descriptions

The data used in this study were provincial-level agricultural outputs and inputs of 30 provinces in mainland China for 1984-1993. Because Hainan province was once a part of Guangdong province and its data were not available until 1987, the data of Hainan province from 1987 to 1993 were added to those of Guangdong province in this study.

Most previous studies on China's agricultural productivity used China's gross value of agricultural output (GVAO) as the total value of agricultural production. Instead of using the gross values of all final products from agricultural production, China's GVAO is defined as the sum of the total value of production from farming, forestry, animal husbandry, fishing, and sideline activities. The values of all inputs in agricultural production are also included in the GVAO. Instead of the GVAO, the net or added value of agricultural output (NVAO) is used to measure the total value of China's aggregate agricultural output in this study. The data on the total net value of agricultural output from farming, forestry, animal husbandry, fishery, and sideline production for 29 provinces and regions were taken from the *China Statistical Yearbook* and the *China Rural Statistical Yearbook*. The time series of provincial NVAO from 1984 to 1993 were adjusted by China's GDP deflator (1990=100), which was obtained from the *International Financial Statistics CD-ROM*.

Land, labor, machinery, fertilizers, and draft animals are considered the five main inputs in Chinese agricultural production. Land refers to the total cultivated areas at the end of each year. The data on provincial cultivated land before 1990 were taken from the *Agricultural Statistics of the People's Republic of China, 1949-1990,* and data for 1991-1993 were obtained from the *China Statistical Yearbook*.

Our measure of labor was the total rural labor force in farming, forestry, animal husbandry, fishery, and sideline production. The labor force in rural industry, construction, transportation, commerce, and miscellaneous occupations was excluded. The data on rural labor were taken from the *China Agriculture Yearbook* and the *China Statistical Yearbook*.

Machinery and draft animals refer to the capital inputs in China's agricultural production in this study. Machinery is measured by the Total Power of Farm Machinery (TPFM). The TPFM includes the total mechanical power of machinery used in farming, forestry, animal husbandry, fishery, and sideline production as such plowing, irrigating, draining, harvesting, farm product processing, agricultural transport, plant protection, and stock breeding.

Draft animals are defined as animals used for field preparation and hauling. The provincial data on the numbers of draft animals for 1984-1990 were taken from the *Agricultural Statistics of the People's Republic of China, 1949-1990*, and the data for the rest of years were obtained from the *China Statistical Yearbook*.

Chemical fertilizers refer to the sum of pure or effective weight of nitrogen, phosphate, potash, and complex fertilizers. The data on total chemical fertilizers consumed by each province for 1987-1993 were obtained from the *China Statistical Yearbook*, and data for the years before 1987 were derived from the *Agricultural Statistics of the People's Republic of China, 1949-1990*.

Arnade (1994) used the number of tractors per agricultural employee, land/labor ratios, and tractor/labor ratios as ranking criteria to classify the agricultural technology category among 77 countries. But all of these rankings are not adequate to reflect the differences of geographical conditions and resource endowments in agricultural production of 29 provinces. In this study, we used GDP per capita as ranking to classify the agricultural production in 29 provinces into two categories of agricultural technology: advanced technology and low technology. The advanced-technology category includes 14 provinces, while 15 provinces were placed in the low-technology category.

The average agricultural outputs and inputs of 29 provinces from 1984 to 1993 are presented in Table 1. Shandong is the largest agricultural province in China, followed closely by Sichuan and Guangdong. Jiangsu, Henan, Hunan, and Hubei are also important for Chinese agriculture. Tibet has the smallest agricultural production in China, followed by Ningxia and Qinghai.

Table 1. Average Agricultural Output and Inputs by Province, 1984-93

Province	Net Output (100 million RMB)	Cultivated Land (1,000 ha)	Rural Labor (10,000)	Machinery (10,000 kw)	Fertilizers (10,000 ton)	Draft Animals (10,000 hd)
Advanced-Technology Province						
Beijing	35.63	414.77	73.58	383.11	11.76	13.38
Tianjing	25.90	436.80	80.70	405.20	6.04	23.30
Hebei	196.78	6571.41	1556.92	2558.64	137.89	375.39
Liaoning	150.22	3499.08	537.82	960.55	78.39	220.59
Jilin	103.88	3960.56	448.95	557.33	72.29	195.77
Helongjiang	131.62	8872.80	401.68	1090.83	65.81	196.48
Shanghai	29.74	326.41	72.51	243.62	17.63	1.16
Jiangsu	322.64	4565.19	1504.32	1946.45	202.04	65.27
Zhejiang	209.81	1733.95	1161.81	1090.25	86.34	48.25
Fujian	136.99	1243.33	682.85	535.93	70.32	91.53
Shandong	397.90	6909.63	2230.42	3230.57	234.88	488.24
Hubei	244.99	3502.56	1263.18	1059.04	131.04	256.06
Guangdong*	373.85	2958.11	1550.17	1302.85	152.85	408.48
Xinjiang	80.94	3095.21	238.76	481.36	33.79	206.13
Low-Technology Province						
Shanxi	65.84	3720.35	543.48	979.40	50.47	207.97
Inner	92.42	4968.85	427.60	667.54	29.61	250.68
Anhui	216.69	4378.77	1675.16	1168.00	133.67	369.36
Jiangxi	147.38	2354.41	979.28	605.57	74.48	235.07
Henan	282.88	6959.57	2462.54	2054.14	189.50	751.89
Hunan	249.15	3319.77	1925.32	1130.99	118.66	290.86
Guangxi	151.25	2583.97	1388.76	695.06	75.39	462.44
Sichuan	375.90	6317.52	3681.53	1172.79	171.03	440.48
Guizhou	83.44	1854.40	1227.62	276.05	41.44	438.23
Yunnan	125.55	2818.71	1315.14	594.15	54.03	485.97
Tibet	12.47	223.00	76.93	43.23	1.27	117.45
Shaanxi	98.71	3555.79	872.88	656.62	60.13	194.48
Gansu	56.02	3484.94	583.16	536.67	30.59	341.17
Qinghai	15.17	572.30	104.71	116.04	4.62	63.88
Ningxia	14.60	797.56	108.47	169.30	9.77	55.91

* Hainan Province is included in Guangdong Province.

To see the changes in Chinese agricultural production during the 1984-93 period, we summarize the average annual growth rates of output and inputs in agricultural production for each province in Table 2. Among the advanced-technology provinces, Liaoning and Fujian had the highest average annual growth rates in output (10 percent), followed by Guangdong (8.7 percent). Shanghai had the lowest growth rate (1.8 percent) and followed Hubei (4 percent). Guangxi had the highest agricultural production growth (8.8 percent) among low-technology provinces, followed by Shanxxi (7.8 percent) and Yunnan (6.8 percent). While Tibet experienced the lowest agricultural production growth among the low-technology provinces, advanced-technology provinces had higher average agricultural production growth than low-technology provinces over the sample period.

Among the input factors, the use of chemical fertilizers in agricultural production had the highest growth rates for both technology categories, followed by the uses of machinery and draft animals. Advanced-technology provinces had smaller growth rates in use of these inputs than low-technology provinces in agricultural production. Six advanced-technology provinces, which are the most developed areas in China, had negative growth rates of labor force used in agricultural production. Despite migration of the rural labor force to the urban areas since Chinese economic reforms, the average growth rate of labor force used in agricultural production was still close to 1.7 percent for low-technology provinces and 0.03 percent for advanced-technology provinces during the 1984-93 period. Rapid economic growth and industrialization in China reduced its cultivated land by 0.5 percent for advanced-technology provinces, which is higher than 0.1 percent of negative growth rate for low-technology provinces. Shanghai and Guangdong, the two most prosperous regions in China, had the highest decreasing rates of cultivated land. Only six provinces in the remote area (Inner Mongolia, Guangxi, Yunnan, Tibet, Ningxia, and Xinjiang) increased their cultivated land use in agricultural production during these years . For Shanghai, chemical fertilizers is the only one input which had a positive growth rate, while the use of the other four factors declined at the highest rates in the country. This may be the reason why Shanghai had the lowest growth rate in agricultural production in China. Lower output growth rate and higher input growth rates for low-technology provinces may imply poorer performance in agricultural production with a lower agricultural productivity.

Results and Implications for Chinese Agriculture

As indicated by Färe et al. (1994), the distance function is equivalent to the inverse of Farrell's measure of output efficiency. We use this index, which is defined as the reciprocal of (4), to measure the technical efficiency in agricultural sector for each province of China during the 1984-93 period. We constructed the best-practice frontiers in agricultural production from both technology categories for each year and then compared the individual provinces to the best frontier with the same technology. If one province's index value is equal to one, the agricultural production of this province is on the best-practice frontier or technically efficient. If the index value is greater than one, its production is below the best-practice frontier or technically inefficient.

Table 2. Average Annual Growth Rates of Agricultural Output and Inputs by Province, 1984-93

Province	Net Output	Cultivated Land	Rural Labor	Machinery	Fertilizer	Draft Animals
			Advanced-Technology Province			
Beijing	0.07587	-0.00445	-0.02554	0.04320	0.08057	0.08622
Tianjing	0.06380	-0.00517	-0.01170	0.04245	0.08947	0.03337
Hebei	0.04575	-0.00128	0.01493	0.05810	0.07395	0.02484
Liaoning	0.10005	-0.00555	0.00156	0.02104	0.03848	0.00469
Jilin	0.07139	-0.00193	0.04278	0.02927	0.06888	0.00374
Helongjiang	0.06845	-0.00023	0.01358	0.02582	0.11570	0.02255
Shanghai	0.01823	-0.01454	-0.06776	-0.02533	0.07446	-0.11279
Jiangsu	0.04842	-0.00298	-0.00551	0.02647	0.05934	-0.00050
Zhejiang	0.04695	-0.00836	-0.00177	0.06952	0.02559	-0.04245
Fujian	0.10036	-0.00420	0.01954	0.07842	0.08345	0.00762
Shandong	0.04693	-0.00504	0.01194	0.12212	0.08657	0.09208
Hubei	0.03997	-0.00686	0.00909	0.02318	0.09083	0.00906
Guangdong*	0.08455	-0.01046	-0.00828	0.07853	0.06516	0.00857
Xinjiang	0.06009	0.00154	0.01067	0.05651	0.12428	0.01037
Average	**0.06220**	**-0.00497**	**0.00025**	**0.04638**	**0.07691**	**0.01053**
			Low-Technology Province			
Shanxi	0.04134	-0.00308	0.01580	0.04718	0.06905	0.01446
Inner Mongolia	0.06430	0.00605	0.00986	0.07196	0.11083	-0.00287
Anhui	0.04785	-0.00299	0.01525	0.07846	0.05864	0.00894
Jiangxi	0.05538	-0.00227	0.00784	0.02863	0.07305	0.04596
Henan	0.04156	-0.00292	0.01607	0.06390	0.09468	0.03056
Hunan	0.04816	-0.00259	0.01097	0.05422	0.06579	0.01989
Guangxi	0.08741	0.00210	0.01039	0.08748	0.09284	0.03840
Sichuan	0.04603	-0.00269	0.01073	0.05254	0.06270	0.01624
Guizhou	0.05090	-0.00188	0.03394	0.08242	0.10062	0.03495
Yunnan	0.06796	0.00348	0.02709	0.07330	0.09012	0.02147
Tibet	0.03317	0.00004	0.00433	0.07214	0.18425	0.09852
Shaanxi	0.07835	-0.00592	0.02246	0.03157	0.10339	0.01158
Gansu	0.06248	-0.00037	0.02219	0.05063	0.10097	0.02551
Qinghai	0.04713	0.00358	0.02165	0.07070	0.09432	0.01040
Ningxia	0.04392	0.00125	0.02667	0.07069	0.11300	-0.00046
Average	**0.05440**	**-0.00055**	**0.01702**	**0.06239**	**0.09428**	**0.02490**

* Hainan Province is included in Guangdong Province.

The technical efficiency indexes under the constant returns to scale of 29 provinces from 1984 to 1993 are presented in Table 3. Among the advanced-technology provinces, five of them (Beijing, Tianjing, Shanghai, Zhejiang, and Guangdong) were consistently efficient and lie on the best-practice frontier during this period. Shandong was the most technically inefficient province in agricultural production within the advanced-technology category, followed by Jilin and Helongjiang. Fujian was efficient for most years, except two years in the mid 1980s. Xinjiang was also efficient in the 1980s, but became inefficient in the last two years of the sample.

Only five provinces with low agricultural technology (Inner Mongolia, Jiangxi, Hunan, Sichuan, and Tibet) consistently lie on the best-practice frontier during the 1984-93 period. Guizhou and Qinghai were also efficient in most years, except 1993. Shanxi was the most inefficient province in agricultural production among the low-technology provinces, followed closely by Ningxia and Ningxia.

In this study, we decomposed the Malmquist productivity index into the technical change indexes (TECHCH) and efficiency change (EFFCH) index. In order to identify change in scale efficiency, EFFCH was further decomposed into PEEFCH and SCH. To obtain the Malmquist productivity indexes and other indexes for each province and each pair of years, we used the DEA approach to calculate the output distance functions by solving 1,566 nonparametric linear programming problems. But due to limited space in this paper, we only present the average annual changes of the Malmquist productivity indexes and their components for each province during the 1984-93 period in Table 4. Any improvement in productivity implies that the value of Malmquist index is greater than 1.

The results showed that the average productivity growth (MALM) in agricultural production averaged at 3.7 and 2.1 percent for provinces with advanced technology and low technology, respectively. Higher productivity growth for advanced-technology provinces reflects their higher growth rates in output and lower growth rates in the uses of all five inputs. On average, the technical change index (TECHCH) also rose 4.7 percent for advanced-technology provinces and 2.7 percent for low-technology provinces. Meanwhile, the efficiency change index (EFFCH) declined 0.8 and 0.4 percent for advanced-technology provinces and low-technology provinces, respectively. Growth in technical change and decline in technical efficiency suggest that increased TFP in Chinese agricultural production arose from the innovation in technology rather than the improvement in technical efficiency. The decrease in technical efficiency was partially due to the decline in scale efficiency and as well as the fall in pure efficiency.

Table 3. Technical Efficiency Indexes Under Constant Returns to Scale by Province, 1984-93

Province	Year										**Average**
	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	**1984-93**
					Advanced-Technology Province						
Beijing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Tianjing	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Hebei	1.0557	1.1632	1.2182	1.2108	1.3100	1.0696	1.2239	1.2319	1.2371	1.2435	**1.1964**
Liaoning	1.0000	1.2238	1.0886	1.0983	1.0973	1.3481	1.1217	1.1521	1.1161	1.0252	**1.1271**
Jilin	1.0000	1.0223	1.0750	1.0069	1.2206	1.5720	1.1838	1.3048	1.3457	1.3729	**1.2104**
Helongjiang	1.0000	1.0000	1.0000	1.1555	1.4269	1.5636	1.0756	1.2510	1.1444	1.2153	**1.1832**
Shanghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Jiangsu	1.0000	1.0214	1.0000	1.0317	1.0000	1.0762	1.0000	1.0883	1.0000	1.0073	**1.0225**
Zhejiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Fujian	1.0000	1.0000	1.0954	1.0590	1.0004	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0155**
Shandong	1.0591	1.2418	1.2754	1.3360	1.9482	1.5988	1.4913	1.3745	1.5094	1.8258	**1.4660**
Hubei	1.0000	1.0333	1.0400	1.0975	1.2209	1.2121	1.0683	1.1966	1.1699	1.1964	**1.1235**
Guangdong*	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Xinjiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0306	1.1458	**1.0176**
Average	**1.0082**	**1.0504**	**1.0566**	**1.0711**	**1.1589**	**1.1743**	**1.0832**	**1.1142**	**1.1109**	**1.1452**	1.0973
					Low-Technology Province						
Shanxi	1.0558	1.2515	1.5367	1.6952	1.6920	1.3292	1.3960	1.7634	1.5767	1.5846	**1.4881**
Inner Mongolia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Anhui	1.0490	1.0256	1.0000	1.0132	1.0000	1.0003	1.1718	1.5710	1.3015	1.1226	**1.1255**
Jiangxi	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Henan	1.1464	1.2810	1.3601	1.1286	1.3344	1.1597	1.3796	1.4262	1.5185	1.5232	**1.3258**
Hunan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Guangxi	1.2692	1.2965	1.2416	1.2456	1.2417	1.0748	1.1284	1.1235	1.0283	1.0593	**1.1709**
Sichuan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Guizhou	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0724	**1.0072**
Yunnan	1.2134	1.3815	1.3134	1.2466	1.3457	1.1524	1.0000	1.1428	1.1451	1.2739	**1.2215**
Tibet	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	**1.0000**
Shaanxi	1.2464	1.3919	1.3630	1.0000	1.2898	1.2424	1.3774	1.3341	1.3664	1.2964	**1.2908**
Gansu	1.7241	1.8301	1.6594	1.5277	1.7721	1.6822	1.7583	1.8249	1.6863	1.6960	**1.7161**
Qinghai	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0877	**1.0088**
Ningxia	1.2207	1.3398	1.1587	1.3242	1.3776	1.2546	1.4540	1.4341	1.5495	1.6203	**1.3734**
Average	**1.1283**	**1.1865**	**1.1755**	**1.1454**	**1.2036**	**1.1264**	**1.1777**	**1.2413**	**1.2115**	**1.2224**	1.1819

* Hainan Province is included in Guangdong Province.

Table 4. Average Annual Changes of Malmquist Indexes by Province and Technology, 1984-93

Province	Rank	Malmquist Index (MALM)	Technical Change (TECHCH)	Efficiency Change (EFFCH)	Pure Efficiency Change (PEFFCH)	Scale Change (SCH)
				Advanced-Technology Province		
Beijing	1	1.0790	1.0790	1.0000	1.0000	1.0000
Tianjing	10	1.0215	1.0215	1.0000	1.0000	1.0000
Hebei	9	1.0271	1.0466	0.9862	0.9916	0.9945
Liaoning	4	1.0621	1.0564	1.0049	1.0033	0.9986
Jilin	13	1.0094	1.0347	0.9759	0.9821	0.9938
Helongjiang	11	1.0178	1.0274	0.9929	0.9990	0.9879
Shanghai	2	1.0744	1.0744	1.0000	1.0000	1.0000
Jiangsu	7	1.0370	1.0361	1.0008	1.0000	1.0008
Zhejiang	6	1.0389	1.0389	1.0000	1.0000	1.0000
Fujian	5	1.0476	1.0462	1.0007	1.0000	1.0007
Shandong	14	0.9890	1.0494	0.9533	0.9936	0.9594
Hubei	8	1.0303	1.0507	0.9826	0.9858	0.9972
Guangdong*	3	1.0641	1.0641	1.0000	1.0000	1.0000
Xinjiang	12	1.0142	1.0287	0.9855	0.9887	0.9969
Average		**1.0366**	**1.0467**	**0.9916**	**0.9960**	**0.9950**
				Low-Technology Province		
Shanxi	11	1.0170	1.0553	0.9663	0.9674	0.9988
Inner Mongolia	8	1.0237	1.0237	1.0000	1.0000	1.0000
Anhui	4	1.0362	1.0356	1.0016	1.0016	1.0000
Jiangxi	3	1.0366	1.0366	1.0000	1.0000	1.0000
Henan	9	1.0209	1.0511	0.9758	0.9908	0.9827
Hunan	7	1.0248	1.0248	1.0000	1.0000	1.0000
Guangxi	1	1.0448	1.0242	1.0220	1.0200	1.0028
Sichuan	13	1.0022	1.0022	1.0000	1.0000	1.0000
Guizhou	15	0.9811	0.9882	0.9925	0.9952	0.9972
Yunnan	12	1.0068	1.0116	1.0002	0.9990	1.0004
Tibet	5	1.0352	1.0352	1.0000	1.0000	1.0000
Shaanxi	2	1.0408	1.0340	1.0064	1.0079	0.9970
Gansu	10	1.0182	1.0204	1.0048	1.0102	0.9960
Qinghai	14	0.9940	1.0032	0.9910	1.0000	0.9910
Ningxia	6	1.0265	1.0612	0.9734	1.0000	0.9734
Average		**1.0206**	**1.0271**	**0.9956**	**0.9995**	**0.9960**

* Hainan Province is included in Guangdong Province.

Among the total 29 provinces, three provinces, Shandong and Qinghai with advanced-technology and Guizhou with low-technology, had negative average growth rates in total productivity from 1984 to 1993. Shandong had the greatest decline in total productivity among advanced-technology provinces because of its poorest performance in technical efficiency. Guizhou was the only province with negative growth in technical change, as well as in the other four indexes, while Guangxi is the only province that had improvement in all five indexes. Only three advanced-technology provinces, Liaoning, Jiangsu, and Fujian, and four low-technology provinces, Anhui, Guangxi, Yunnan, and Gansu, had improvements in both technology and technical efficiency, indicating that Chinese agricultural productivity growth was attributed mostly to technology progress, rather than to improvement of technical efficiency.

For comparison, the results calculated from all 29 provinces based on the assumption of uniform agricultural technology across provinces are presented in Table 5. Beijing experienced the highest growth in both total productivity and technical change, followed by Shanghai and Guangdong. Liaoning had the largest improvement in technical efficiency (EEFCH). Qinghai showed the greatest improvement in pure efficiency over the 1984-1993 period, but it also showed a large decline in scale efficiency. Ningxia had the most gain in scale efficiency, while its pure efficiency suffered the greatest decline in the country. Shandong, the largest agricultural province in China, experienced the largest falls in both technical efficiency and scale efficiency.

Since the Malmquist productivity index and its components are multiplicative, we can calculate the cumulated Malmquist productivity index and its components such as the cumulated technical change index and the cumulated efficiency change index for each province as the sequential multiplicative sum of the annual indexes. Table 6 presents the cumulated Malmquist productivity index and its components under the constant returns to scale from 1984 to 1993. The cumulated indexes measure the total changes in TFP, technical efficiency, and technology over the 1984-93 time period. We also can plot the cumulated productivity indexes against time to see the patterns of the changes in these indexes.

In this study, we only illustrated the cumulated indexes under constant returns to scale for four provinces from each agricultural technology category: Beijing, Liaoning, Jilin, and Shandong (advanced-technology); Henan, Guangxi, Sichuan, and Guizhou (low-technology). Among advanced-technology provinces, Beijing had the highest growths in productivity and technology and was consistently on the best-practice frontier over the 1984-93 period (Figure 1). Liaoning had improvement in total productivity, technology, and efficiency and showed increasing trends in all these three indexes (Figure 2). Jilin had a decline in efficiency, but its consistent technical progress still increased in its total factor productivity (Figure 3). Shandong had the largest decline in efficiency in China during this period. The poorest efficiency in production caused a decrease in its productivity, even though its growth in technical change was among the best in the country (Figure 4).

Table 5. Average Annual Changes of Malmquist Indexes Under Homogenous Technology by Province, 1984-93

Province	Rank	Malmquist Index (MALM)	Technical Change (TECHCH)	Efficiency Change (EFFCH)	Pure Efficiency Change (PEFFCH)	Scale Change (SCH)
Beijing	1	1.0794	1.0794	1.0000	1.0000	1.0000
Tianjing	10	1.0229	1.0229	1.0000	1.0000	1.0000
Hebei	25	0.9860	1.0327	0.9623	0.9591	1.0020
Shanxi	28	0.9755	1.0270	0.9565	0.9530	1.0010
Inner Mongolia	23	0.9909	1.0125	0.9795	0.9843	0.9965
Liaoning	4	1.0621	1.0564	1.0049	1.0033	0.9986
Jilin	14	1.0094	1.0347	0.9759	0.9788	0.9970
Helongjiang	12	1.0177	1.0273	0.9929	0.9990	0.9879
Shanghai	2	1.0744	1.0744	1.0000	1.0000	1.0000
Jiangsu	7	1.0370	1.0361	1.0008	1.0000	1.0008
Zhejiang	6	1.0391	1.0391	1.0000	1.0000	1.0000
Anhui	21	0.9928	1.0293	0.9641	0.9614	1.0017
Fujian	5	1.0498	1.0485	1.0007	1.0000	1.0007
Jiangxi	13	1.0107	1.0143	1.0005	1.0009	0.9999
Shandong	24	0.9895	1.0498	0.9531	0.9936	0.9593
Henan	29	0.9736	1.0261	0.9561	0.9801	0.9723
Hubei	9	1.0304	1.0514	0.9819	0.9839	0.9984
Hunan	22	0.9916	1.0175	0.9775	0.9751	1.0025
Guangdong*	3	1.0678	1.0662	1.0014	1.0000	1.0014
Guangxi	15	1.0027	1.0067	1.0031	0.9953	1.0064
Sichuan	19	0.9988	0.9989	1.0000	1.0000	1.0000
Guizhou	27	0.9771	0.9843	0.9925	0.9952	0.9972
Yunnan	20	0.9986	1.0196	0.9878	0.9759	1.0125
Tibet	8	1.0333	1.0333	1.0000	1.0000	1.0000
Shaanxi	18	0.9991	1.0105	0.9958	0.9937	1.0003
Gansu	17	1.0010	1.0258	0.9844	0.9888	0.9981
Qinghai	16	1.0010	1.0246	0.9910	1.0078	0.9880
Ningxia	26	0.9785	1.0310	0.9504	0.9433	1.0264
Xinjiang	11	1.0211	1.0310	0.9901	0.9919	0.9982
Average		**1.0142**	**1.0314**	**0.9863**	**0.9884**	**0.9982**

* Hainan Province is included in Guangdong Province.

Table 6. Cumulated Malmquist Indexes Under Constant Returns to Scale by Province, 1984-93

Province	Rank	Malmquist Index (MALM)	Technical Change (TECHCH)	Efficiency Change (EFFCH)	Pure Efficiency Change (PEFFCH)	Scale Change (SCH)
				Advanced-Technology Province		
Beijing	1	1.8418	1.8418	1.0000	1.0000	1.0000
Tianjing	10	1.1339	1.1339	1.0000	1.0000	1.0000
Hebei	9	1.2562	1.4799	0.8489	0.9021	0.9413
Liaoning	4	1.5810	1.6210	0.9755	0.9999	0.9754
Jilin	12	0.9604	1.3186	0.7284	0.7708	0.9450
Helongjiang	11	1.0093	1.2264	0.8228	0.9604	0.8567
Shanghai	2	1.8167	1.8167	1.0000	1.0000	1.0000
Jiangsu	7	1.3597	1.3698	0.9928	1.0000	0.9928
Zhejiang	6	1.3920	1.3920	1.0000	1.0000	1.0000
Fujian	5	1.4940	1.4940	1.0000	1.0000	1.0000
Shandong	14	0.8708	1.5011	0.5800	0.9363	0.6194
Hubei	8	1.2899	1.5434	0.8359	0.8580	0.9742
Guangdong*	3	1.7171	1.7171	1.0000	1.0000	1.0000
Xinjiang	10	1.1151	1.2776	0.8728	0.8982	0.9717
Average		**1.3456**	**1.4809**	**0.9041**	**0.9518**	**0.9483**
				Low-Technology Province		
Shanxi	11	1.0487	1.5738	0.6662	0.6739	0.9889
Inner Mongolia	7	1.1696	1.1696	1.0000	1.0000	1.0000
Anhui	4	1.2587	1.3472	0.9345	0.9447	0.9892
Jiangxi	2	1.3573	1.3573	1.0000	1.0000	1.0000
Henan	8	1.1540	1.5334	0.7526	0.9054	0.8311
Hunan	6	1.2372	1.2372	1.0000	1.0000	1.0000
Guangxi	1	1.4681	1.2253	1.1980	1.1736	1.0211
Sichuan	12	1.0090	1.0090	1.0000	1.0000	1.0000
Guizhou	15	0.8278	0.8877	0.9325	0.9566	0.9748
Yunnan	13	1.0011	1.0513	0.9524	0.9814	0.9706
Tibet	10	1.1007	1.1007	1.0000	1.0000	1.0000
Shaanxi	3	1.2797	1.3308	0.9614	0.9883	0.9728
Gansu	9	1.1509	1.1319	1.0166	1.0742	0.9464
Qinghai	14	0.9223	1.0033	0.9193	1.0000	0.9193
Ningxia	5	1.2394	1.6451	0.7533	1.0000	0.7533
Average		**1.1645**	**1.2572**	**0.9405**	**0.9784**	**0.9606**

* Hainan Province is included in Guangdong Province.

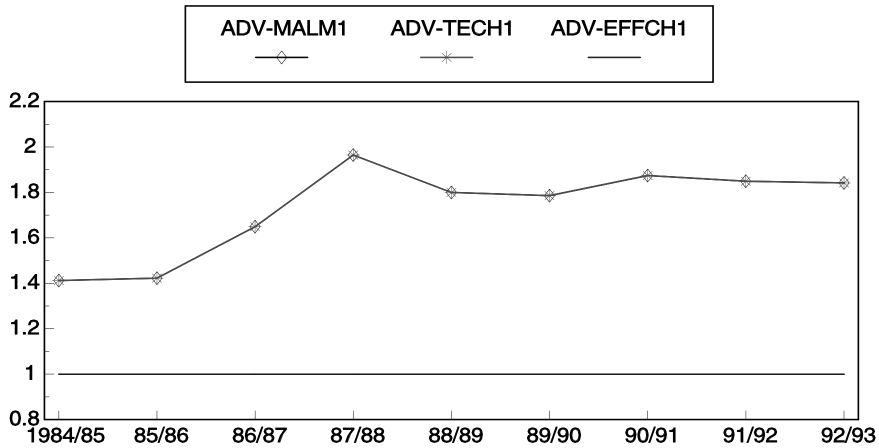

Figure 1. Cumulated Malmquist Indexes Under Constant Returns to Scale, Beijing (Advanced-Technology)

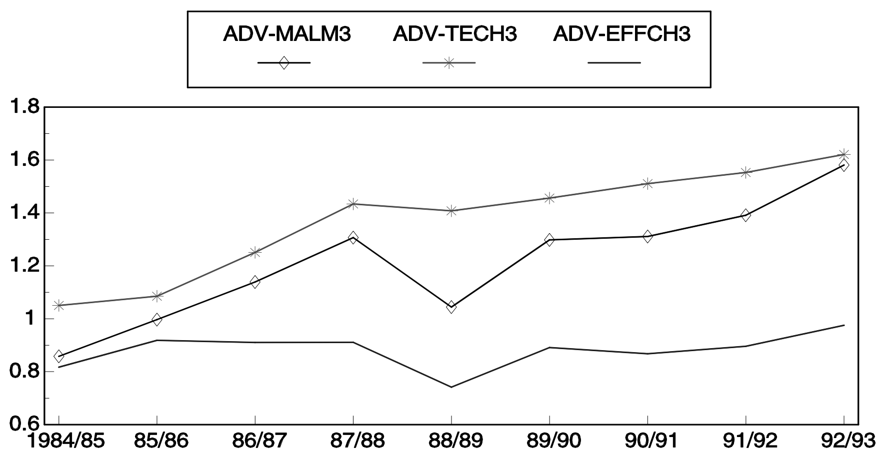

Figure 2. Cumulated Malmquist Indexes Under Constant Returns to Scale, Liaoning (Advanced-Technology)

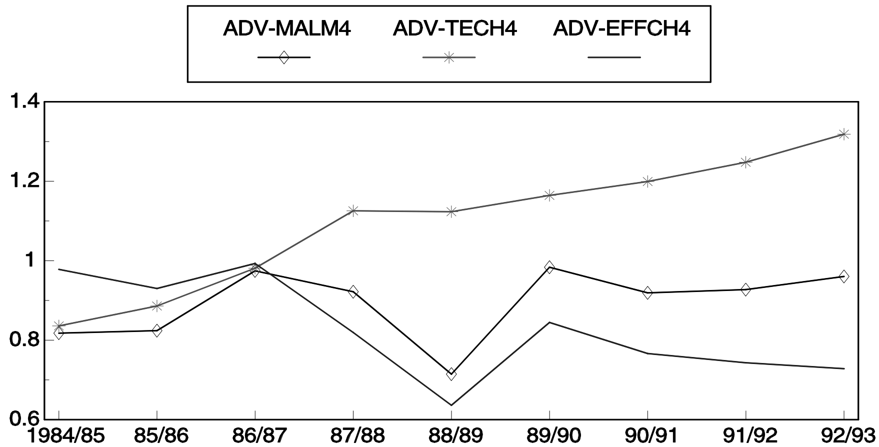

Figure 3. Cumulated Malmquist Indexes Under Constant Returns to Scale, Jilin (Advanced-Technology)

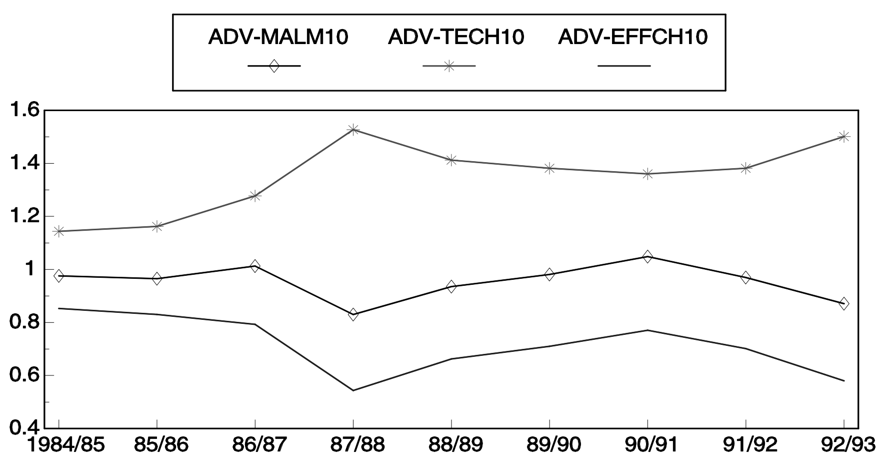

Figure 4. Cumulated Malmquist Indexes Under Constant Returns to Scale, Shandong (Advanced-Technology)

Among low-technology provinces, Henan had similar patterns to Jilin with growths in productivity and technical change and decline in efficiency (Figure 5). Guangxi experienced the greatest improvement in technical efficiency and was the only province with a productivity index line (LOW-MALM8) above the other two index lines (LOW-TECH8 and LOW-EFFCH8) for the most sample years (Figure 6). Sichuan, the largest agricultural province within the low-technology category, consistently lays on the best-practice frontier in agricultural production. However, it also had negative growths in technical change for the most years. The slow technical progress resulted in very little improvement in its agricultural productivity (Figure 7). Guizhou was the only one province with declines in all three indexes because of its technical degrees in agricultural production (Figure 8).

Arnade (1994) found that a decline in total factor agricultural productivity is associated with a significant increase in single-factor productivity in many developing countries. It is also interesting to look at the single-factor productivity indexes in agricultural production of all provinces. The land and labor productivity indexes of all 29 provinces over the 1984-93 period are reported in Tables 7 and 8, respectively. These indexes were calculated by dividing total agricultural output by the appropriate input. All provinces showed increases in land and labor productivity over the this period. Beijing and Shanghai had the highest average labor productivity, while Guizhou's labor productivity was the lowest. Guangdong and Zhejiang had the highest land productivity, while Gansu had the lowest. Comparing the single-factor productivity indexes between two agricultural technology categories, advanced-technology provinces had much higher productivity in both land and labor productivity indexes than did the low-technology provinces.

Comparing the single-factor productivity indexes with the Malmquist TFPI in Table 4, 11 provinces showed increases in land and labor productivity, but declines in TFP because of declines in technical efficiency. This result is similar to those in many developing countries. Arnade (1994) argued that increased technical change associated with decline in efficiency may arise from the unfamiliarity with new technology.

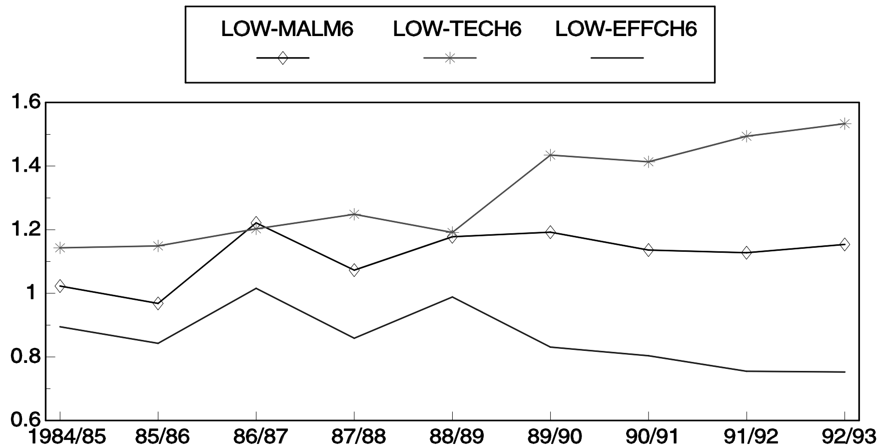

Figure 5. Cumulated Malmquist Indexes Under Constant Returns to Scale, Henan (Low-Technology)

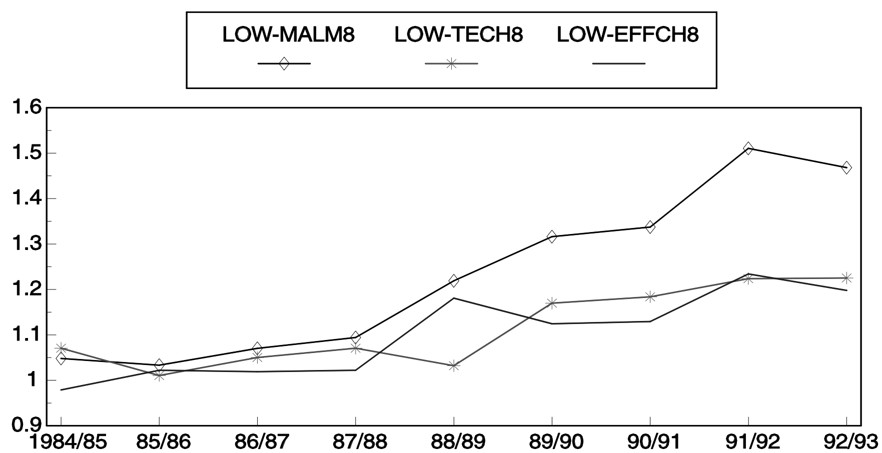

Figure 6. Cumulated Malmquist Indexes Under Constant Returns to Scale, Guangxi (Low-Technology)

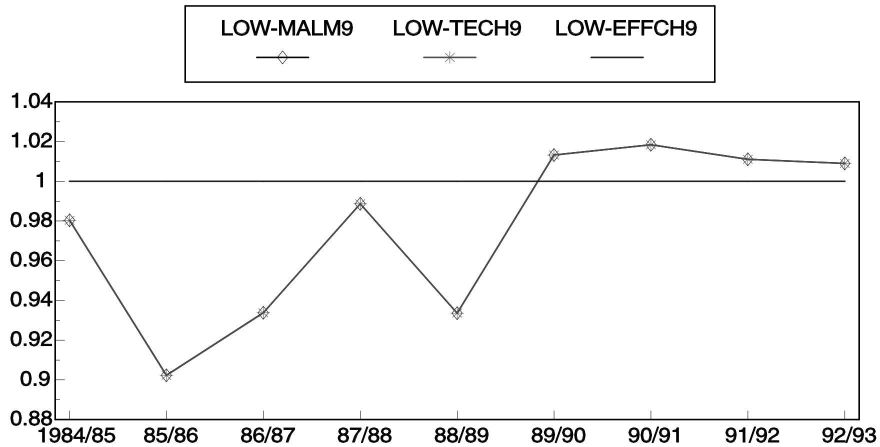

Figure 7. Cumulated Malmquist Indexes Under Constant Returns to Scale, Sichuan (Low-Technology)

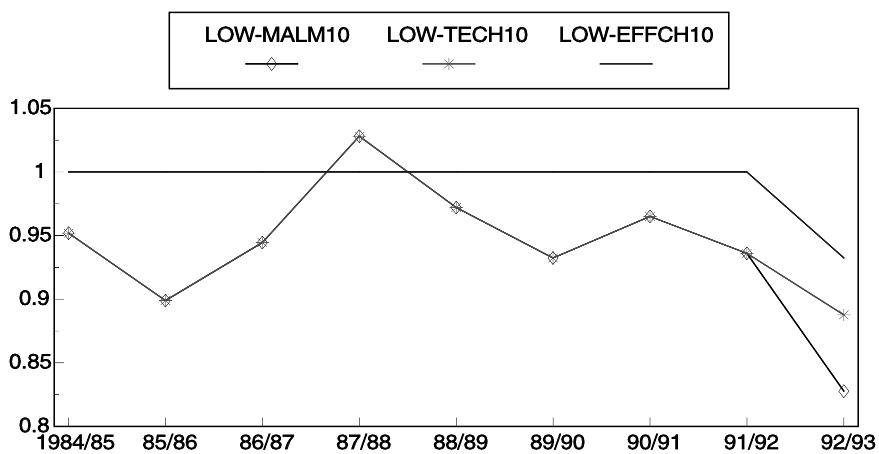

Figure 8. Cumulated Malmquist Indexes Under Constant Returns to Scale, Guizhou (Low-Technology)

Table 7. Single-factor Productivity by Province: Land Productivity, 1984-93

Province	Year										Average
	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1983-94
	Advanced-Technology Province										
Beijing	0.0536	0.0590	0.0607	0.0737	0.1017	0.0972	0.1039	0.1061	0.1017	0.1035	**0.0861**
Tianjing	0.0380	0.0395	0.0521	0.0572	0.0669	0.0719	0.0705	0.0684	0.0658	0.0647	**0.0595**
Hebei	0.0255	0.0254	0.0249	0.0265	0.0267	0.0316	0.0340	0.0336	0.0352	0.0362	**0.0300**
Liaoning	0.0332	0.0282	0.0346	0.0403	0.0467	0.0382	0.0481	0.0494	0.0524	0.0596	**0.0431**
Jilin	0.0231	0.0199	0.0216	0.0262	0.0268	0.0220	0.0318	0.0292	0.0303	0.0316	**0.0263**
Helongjiang	0.0149	0.0119	0.0138	0.0127	0.0123	0.0115	0.0181	0.0168	0.0183	0.0179	**0.0148**
Shanghai	0.0763	0.0778	0.0757	0.0877	0.0958	0.1010	0.1052	0.0979	0.0973	0.0992	**0.0914**
Jiangsu	0.0573	0.0584	0.0638	0.0677	0.0775	0.0724	0.0759	0.0702	0.0786	0.0855	**0.0707**
Zhejiang	0.0880	0.0980	0.1040	0.1169	0.1278	0.1268	0.1283	0.1378	0.1366	0.1500	**0.1214**
Fujian	0.0676	0.0761	0.0779	0.0931	0.1110	0.1176	0.1208	0.1300	0.1446	0.1669	**0.1105**
Shandong	0.0473	0.0468	0.0481	0.0528	0.0551	0.0551	0.0616	0.0719	0.0693	0.0692	**0.0577**
Hubei	0.0529	0.0563	0.0618	0.0676	0.0718	0.0724	0.0824	0.0763	0.0796	0.0802	**0.0701**
Guangdong*	0.0684	0.0869	0.0955	0.1115	0.1343	0.1406	0.1440	0.1489	0.1629	0.1792	**0.1272**
Xinjiang	0.0174	0.0195	0.0204	0.0238	0.0273	0.0272	0.0305	0.0331	0.0323	0.0299	**0.0261**
Average	**0.0474**	**0.0503**	**0.0539**	**0.0613**	**0.0701**	**0.0704**	**0.0754**	**0.0764**	**0.0789**	**0.0838**	0.0668
	Low-Technology Province										
Shanxi	0.0181	0.0162	0.0135	0.0132	0.0161	0.0192	0.0222	0.0175	0.0204	0.0208	**0.0177**
Inner Mongolia	0.0133	0.0150	0.0147	0.0160	0.0209	0.0187	0.0219	0.0213	0.0215	0.0224	**0.0186**
Anhui	0.0394	0.0441	0.0467	0.0508	0.0543	0.0534	0.0549	0.0405	0.0507	0.0604	**0.0495**
Jiangxi	0.0461	0.0495	0.0515	0.0574	0.0585	0.0601	0.0748	0.0748	0.0777	0.0760	**0.0627**
Henan	0.0333	0.0343	0.0328	0.0411	0.0376	0.0436	0.0461	0.0454	0.0458	0.0468	**0.0407**
Hunan	0.0578	0.0621	0.0666	0.0721	0.0718	0.0736	0.0828	0.0842	0.0884	0.0919	**0.0751**
Guangxi	0.0388	0.0421	0.0444	0.0489	0.0522	0.0602	0.0675	0.0699	0.0801	0.0802	**0.0584**
Sichuan	0.0481	0.0495	0.0492	0.0547	0.0579	0.0580	0.0668	0.0697	0.0702	0.0717	**0.0596**
Guizhou	0.0376	0.0380	0.0408	0.0453	0.0517	0.0511	0.0518	0.0572	0.0574	0.0567	**0.0487**
Yunnan	0.0319	0.0336	0.0346	0.0376	0.0418	0.0429	0.0572	0.0547	0.0575	0.0526	**0.0444**
Tibet	0.0397	0.0541	0.0470	0.0433	0.0541	0.0513	0.0619	0.0705	0.0719	0.0655	**0.0559**
Shaanxi	0.0211	0.0203	0.0213	0.0323	0.0268	0.0276	0.0299	0.0313	0.0327	0.0352	**0.0278**
Gansu	0.0114	0.0123	0.0136	0.0151	0.0171	0.0160	0.0184	0.0181	0.0192	0.0197	**0.0161**
Qinghai	0.0195	0.0210	0.0241	0.0251	0.0285	0.0285	0.0299	0.0292	0.0300	0.0291	**0.0265**
Ningxia	0.0141	0.0149	0.0171	0.0163	0.0192	0.0196	0.0206	0.0208	0.0202	0.0203	**0.0183**
Average	**0.0311**	**0.0334**	**0.0343**	**0.0378**	**0.0386**	**0.0418**	**0.0470**	**0.0471**	**0.0495**	**0.0500**	0.0413

* Hainan Province is included in Guangdong Province.

Table 8. Single-factor Productivity by Province: Labor Productivity, 1984-93

	Year										Average
Province	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1983-94
					Advanced-Technology Province						
Beijing	0.1751	0.2754	0.2956	0.3618	0.5230	0.4835	0.5197	0.5435	0.5574	0.5753	**0.4310**
Tianjing	0.1258	0.1853	0.2512	0.2791	0.3338	0.3483	0.3398	0.3283	0.3200	0.3207	**0.2832**
Hebei	0.0984	0.1022	0.1000	0.1073	0.1066	0.1216	0.1253	0.1196	0.1243	0.1283	**0.1134**
Liaoning	0.1891	0.1718	0.2056	0.2405	0.2803	0.2235	0.2753	0.2732	0.2957	0.3434	**0.2499**
Jilin	0.2480	0.1990	0.2001	0.2335	0.2158	0.1676	0.2317	0.2107	0.2104	0.2234	**0.2140**
Helongjiang	0.3108	0.2508	0.2877	0.2688	0.2614	0.2276	0.3452	0.3082	0.3501	0.3380	**0.2949**
Shanghai	0.1393	0.2379	0.2596	0.3317	0.3934	0.4293	0.4533	0.4523	0.4679	0.4754	**0.3640**
Jiangsu	0.1349	0.1579	0.1780	0.1915	0.2185	0.1962	0.2017	0.1834	0.2102	0.2365	**0.1909**
Zhejiang	0.1118	0.1379	0.1443	0.1619	0.1760	0.1678	0.1654	0.1752	0.1725	0.2011	**0.1614**
Fujian	0.1213	0.1385	0.1380	0.1598	0.1862	0.1945	0.1935	0.1970	0.2158	0.2519	**0.1797**
Shandong	0.1360	0.1391	0.1424	0.1545	0.1584	0.1549	0.1683	0.1857	0.1792	0.1801	**0.1599**
Hubei	0.1350	0.1522	0.1639	0.1754	0.1818	0.1778	0.1971	0.1776	0.1877	0.1913	**0.1740**
Guangdong*	0.1143	0.1513	0.1655	0.1932	0.2306	0.2379	0.2418	0.2500	0.2746	0.3069	**0.2166**
Xinjiang	0.2103	0.2345	0.2427	0.2820	0.3222	0.3178	0.3501	0.3774	0.3719	0.3349	**0.3044**
Average	**0.1607**	**0.1810**	**0.1982**	**0.1982**	**0.2563**	**0.2467**	**0.2720**	**0.2702**	**0.2813**	**0.2934**	**0.2358**
					Low-Technology Province						
Shanxi	0.1109	0.1081	0.0882	0.0855	0.1020	0.1181	0.1314	0.1003	0.1175	0.1197	**0.1082**
Inner Mongolia	0.1429	0.1601	0.1565	0.1689	0.2218	0.1981	0.2278	0.2128	0.2206	0.2320	**0.1942**
Anhui	0.0990	0.1130	0.1169	0.1266	0.1318	0.1253	0.1247	0.0895	0.1103	0.1341	**0.1171**
Jiangxi	0.1030	0.1177	0.1201	0.1277	0.1280	0.1254	0.1525	0.1501	0.1599	0.1676	**0.1352**
Henan	0.0920	0.0943	0.0897	0.1110	0.0993	0.1118	0.1133	0.1079	0.1069	0.1109	**0.1037**
Hunan	0.0963	0.1040	0.1139	0.1170	0.1133	0.1105	0.1215	0.1221	0.1300	0.1387	**0.1167**
Guangxi	0.0696	0.0745	0.0771	0.0834	0.0880	0.1002	0.1102	0.1128	0.1306	0.1329	**0.0979**
Sichuan	0.0806	0.0828	0.0804	0.0878	0.0910	0.0880	0.0994	0.1010	0.1019	0.1081	**0.0921**
Guizhou	0.0692	0.0677	0.0729	0.0760	0.0822	0.0776	0.0747	0.0801	0.0785	0.0763	**0.0755**
Yunnan	0.0689	0.0718	0.0719	0.0761	0.0822	0.0825	0.1084	0.1006	0.1039	0.0936	**0.0860**
Tibet	0.1061	0.1445	0.1235	0.1133	0.1426	0.1315	0.1602	0.1825	0.1855	0.1690	**0.1459**
Shaanxi	0.0838	0.0831	0.0862	0.1284	0.1012	0.1017	0.1054	0.1054	0.1077	0.1154	**0.1018**
Gansu	0.0688	0.0752	0.0820	0.0850	0.0910	0.0839	0.0934	0.0910	0.0961	0.1010	**0.0867**
Qinghai	0.1015	0.1109	0.1277	0.1299	0.1449	0.1398	0.1441	0.1376	0.1372	0.1334	**0.1307**
Ningxia	0.1044	0.1088	0.1222	0.1143	0.1324	0.1315	0.1320	0.1286	0.1231	0.1219	**0.1219**
Average	**0.1037**	**0.1130**	**0.1150**	**0.1150**	**0.1282**	**0.1340**	**0.1470**	**0.1439**	**0.1493**	**0.1506**	**0.1307**

* Hainan Province is included in Guangdong Province.

The results obtained from this study have important implications for Chinese agriculture. First, several important agricultural provinces such as Shandong, Hubei, Jilin, Helongjiang, Hebei, and Henan,[1] experienced decline in technical efficiency during the 1984-93 period. This result indicates that China has great potential to increase its agricultural output through improving technical efficiency. Second, agriculture in several low-technology provinces, such as Sichuan, Guangxi, Yunnan, Guizhou, and Tibet, were technically efficient or very close to the efficient. However, these provinces experienced very small growth in agricultural technology during the 1984-93 period. This result implies that technological progress is still very important to agricultural productivity growth for low-technology provinces. Third, if we assume the homogenous agricultural technology for all 29 provinces in China, the results in Table 5 show that only 17 provinces had productivity growth in agricultural production. Most of them are located in the coastal areas where the market economy expanded most rapidly during the 1984-1993 period. Rapid economic growth and less market distortions enhanced farmers' accessibility in these provinces to new technology and seed varieties, market information, and education, which benefits farmers in these provinces by improving their production efficiency. With the continuously expanding market economy and less market distortions, technical efficiency and productivity in agriculture are expected to improve in inland provinces. Fourth, considerable differences between advanced-technology provinces and low-technology provinces in TFP growth as well as in labor productivity growth may suggest an important role of rural education in creating the differences in productivity across provinces. Most provinces with advanced-technology have better education. The rural laborers in these provinces may be willing to learn new skills and to adopt new technology in agricultural production. However, we could not measure the impacts of rural education on TFP because of the lack of provincial data on education.

Summary and Conclusions

This paper applied the DEA approach to measure TFP, technical change, and technical efficiency in the Chinese agricultural sector from 1984 to 1993. According to the ranking of per capita GDP of each province, agricultural production of 29 provinces in China was classified into advanced-technology and low-technology categories. The Malmquist productivity index was used to measure productivity growth. With the DEA approach, productivity growth can be decomposed into two components: technical change and efficiency change. This decomposition allowed us to identify the contributions of

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[1]Under the assumption of homogenous agricultural technology for all 29 provinces in China, 17 provinces experienced decline in technical efficiency during the 1984-1993 period (Table 5), indicating the poor efficiency in Chinese agricultural production.

technical progress and improvement in technical efficiency to productivity growth in Chinese agricultural production.

The DEA approach was used to calculate the component distance functions of the Malmquist index and constructed the best-practice (efficient) frontiers for both agricultural technology categories. The technical change index and the efficiency change index were obtained by comparing each province to the best-practice frontier with the same production technology. The Malmquist productivity index was then calculated as a product of these two indexes.

Among the total 29 provinces in China, 26 provinces experienced agricultural productivity growth during the 1984-1993 period, most of which was due to the improved technological progress in agricultural production. For each technology category, only five provinces were consistently technically efficient in agricultural production. Efficiency changes had little contribution to Chinese agricultural productivity growth. Advanced-technology provinces had higher average productivity and technology growths than low-technology provinces in agricultural production. However, the average decline in technical efficiency in advanced-technology provinces was greater than that in low-technology provinces.

Institutional changes under economic reforms in rural areas were mostly attributed to the productivity growth in Chinese agriculture from 1978 to 1984. This study indicated that technical changes were the most important factor to Chinese agricultural productivity growth in the post-institutional reform era. Enhancing agricultural research and development and rural education to stimulate technical progress will be crucial to Chinese agricultural productivity growth, especially for the provinces with low technology. Poor performance in technical efficiency in many important agricultural provinces indicated a great potential for China to increase agricultural productivity through improved technical efficiency. Furthermore, continuously expanding market economy and enhancing rural education may also help farmers to adopt new technology to improve technical efficiency and productivity.

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