Study of Agricultural Productivity and Its Convergence across China's Regions

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ABSTRACT. Because it has a large, growing population but only a small share of land that can be cultivated, it is important for China to enhance its agricultural productivity through technological progress. Using data envelopment analysis, we decompose productivity into pure technical efficiency change, scale efficiency change, and technological progress. We thereby find that annual growth of agricultural productivity in China is about 2.2 percent. Technological progress improved agricultural productivity at a rate of 4.2 percent annually from 1980 to 2005, but the technology efficiency dampened it by an average of 1.9 percent per year. TFP growth and technological progress are faster in eastern provinces than for those in central and western regions. Relative technology efficiency was stable in eastern provinces but declined in the central and western provinces during the study period. Thus, it was technological progress that boosted the TFP growth in china's agriculture. Tests also reveal that σ convergence existed in Chinese agricultural productivity.

Keywords: Production efficiency; Technology progress; Technology efficiency; DEA approach; σ convergence

JEL classification: Q16; O13; O53

1. Introduction

Making agriculture sustainable has been a critical element of China's economic development plan. The country's economic reform, which started in 1978, brought immediate rapid growth of agriculture. But the growth started to fade after the effects of the Household Responsibility System (HRS) were exhausted in the mid-1980s (Lin 1992; Huang 2004). The average annual growth rate of real agricultural output fell to 4.0 percent during the period 1985 to 1989, compared to a rate of 9.4 percent from 1981 to 1984. Although the annualized growth rate rebounded to 8.4 percent for the period 1992 to 1995, China's agricultural productivity growth has since slowed remarkably. As a result, the nation's rural countryside has been in a period of relative stagnation since 1996 (see Figure 1).

Farming practice in China, as well as modern economic growth theory, has underlined the core role of technology progress in long-term economic growth (Nelson 2001). Because of a scarcity of arable, cultivatable land, environment pressures and a burgeoning population, it is particularly important that Chinese farmers learn to improve agricultural productivity through technological progress, as more than 480 million workers remain in agriculture (nearly 62.95

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percent of the country's total labor force).[2] The continuation of agricultural productivity growth not only lifts farmers' incomes, which eases some fears of potential labor unrest, but also releases some rural labor to non-agricultural sectors. The diversion of agricultural labor into producing non-agricultural products is possibly an important means of maintaining current Chinese economic success (Hu 1998).

The imbalance caused by the dominance of agriculture has become a stylized fact in economic development worldwide. China is no exception. Farming remains a wedge in the wealth gap across China's regions. Rapid manufacturing productivity change during the 1990s coupled with relatively low agricultural productivity change widened the spread of income per capita among the nation's provinces (Wang and Fan 2005). Discovering the causes of the continued imbalance is thus important for bridging the interregional wealth gap. Moreover, improving farm productivity would at least bring agriculturally intensive regions into greater harmony with the rest of China's growing economy.

In this paper we examine regional agriculture productivity in China since 1980 with a focus on its tendency (or lack thereof) to converge. We first review the literature analyzing China's agricultural productivity, and then discuss the analytical approach and the data. The empirical results and the analysis are given in the third section. Then we test the convergence of agricultural productivity among China's regions. Finally, a summary of findings and some ideas for future research on the subject are presented.

2. LITERATURE REVIEW

Agricultural productivity change remains a hot topic internationally. There remains some debate about how to measure productivity, however. Broadly speaking, there are three methods of measurement applied in the study of the agricultural productivity. Many studies have applied the conventional Solow growth accounting and production function approaches. Others have used stochastic frontier models. More recently, however, non-parametric DEA methods have been applied.

Employing county-level data, McMillan, Whalley, and Zhu (1989) studied Chinese agriculture productivity using the growth accounting method. They demonstrated that the early reforms provided incentives to raise productivity by about 78 percent from 1978 to 1984. Remaining improvements in farm income were attributed to rising prices of farm-produced goods. Using Solow's growth model, Zhao (2004) estimated China's agricultural productivity dynamically from 1979 to 2000. He found that the average annual growth rate of technology progress for the period 1980-2000 was 2.3 percent, and improvements in technology accounted for 32 percent of the output growth.

By means of a production function approach, Huang, Sun, and Gong (2005) studied how system-wide rural property reforms in 28 Chinese provinces influenced agricultural productivity from 1949 to 1978. They found that, through the radical change in incentives, different property reforms altered agricultural investment and factor utilization rates, which combined to improve agricultural productivity.

Using the country-level dataset, Zhen, Jiao, and Li (2006) investigated the impact of rural system reform on agriculture growth for 1978-2004, and concluded that HRS helped to grow

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[2] The data are from *China Statistical Yearbook* (2007).

agriculture productivity by 40.0 percent from 1989 to 1995 and government support prompted another increase of 35.8 percent. But the reforms in rural tax policy and state-assisted agriculture policies were the main impetus for agricultural productivity growth from 1996 to 2002. Based upon data by province, Lin (1992) showed that agricultural productivity improvements from 1978 to 1984 were largely (about 47.0 percent of the "improvements") induced by transitions from communal systems to the HRS. Xu (1999) also calculated 1979-1996 agriculture productivity using CES production functions. The result shows that for the entire reform from 1979 through 1996, the average annual growth of TFP in agriculture was about 2.3 percent in China.

Fan (2000) develops a frontier shadow cost function approach to estimate empirically the effects of technological change, technical efficiency and allocative efficiency improvements in Chinese agriculture during the period 1980 to 1993. The results show that technical efficiency improved significantly by 8.5 percent per year from 1980 to 1984. But after 1985, technical efficiency improved very little. Allocative efficiency improved very little over the study period. The rate of technological change accelerated during the first phase of reform (1980-1984), with an annual growth of 13.3 percent per annum, and continued to increase during the second phase reforms from 1985 to 1993. Since both technical and allocative efficiency seemed to have plateaued, technological change should remain the primary source of agricultural growth in the future. Fan suggests that the government should continue to increase its support of public investment in infrastructure and technology such as roads, irrigation, and research and extension to sustain agricultural production growth.[2]

Based on a unique county-level dataset, Chen and Song (2008) use a stochastic production frontier model to examine technical efficiency in China's farming sector. They divide production efficiency into two parts: one caused by the inefficiency relative to the subgroup, the other caused by the technology gap between the subgroup and the full sample. Their results show that although China's easternmost counties have the highest efficiency scores with respect to the regional frontier, its northeastern region leads in terms of agricultural production technology nationwide. Meanwhile, the mean efficiency of northeastern counties is particularly low. Chen and Song's first suggestion is that more attention should be paid to the country's agricultural extension system to disseminate agricultural technology and know-how among and within regions. Second, they suggest that when the ecological differences limit the diffusion of agricultural technology, institutional variables, such as factor markets and rural governance, likely deserve greater attention.

Unfortunately, there are some problems with the conventional Solow and stochastic frontier models. The growth accounting approach requires certain behavioral and system-wide assumptions (such as perfect market and profit maximization), many of which are not suitable for studying China, a country undergoing a process of institutional transition (Yue and Liu 2006). The production function method, on the other hand, requires the specification of a functional form, as well as assumptions of constant returns to scale in farm production, technology efficiency, Hicks-neutral technological innovation, and so on (Arcelus and Arocena 2000). These assumptions are difficult to justify in practice, and the TFP measurements will be biased. Moreover, these conventional methods are flawed since they unrealistically assume that all

[2] This should further improve competitiveness, increase the presence of applied technological talent, and popularize compulsory education, vocational education, and adult education in the rural countryside. In addition, it is imperative for improving rural infrastructure and reducing agricultural taxes.

economic units are technically efficient and hence that TFP growth is synonymous with technical progress. [3]

Stochastic frontier analysis overcomes the deficiencies of the conventional methods of measurement of TFP since it accounts for the existence of technical inefficiency effects that can cause an economic unit to produce below its output potential. But a common problem in the use of the stochastic production frontier analysis is that residuals of the statistical analysis are skewed in a positive manner. The assumption of a positive skewness overlooks one important additional possibility: that of negatively skewed one-sided distributions of inefficiencies, and using the degree of skewness in the error term to measure technological inefficiency builds bias into the inefficiency indicator (Carree 2002). Another strong assumption of this method is that the production frontier shifts neutrally over time with no theoretical reasoning (Mahadevan and Kim 2003).

In contrast with Solow-based approach and stochastic frontier analysis, data envelopment analysis (DEA) is a data-based efficiency-measuring method. This approach obviates the need for the rather restrictive assumptions inherent in the more traditional approaches to the study of TFP comparability across time and countries. No specific production function or market assumptions are needed. In addition, DEA can be formulated so that it decomposes total factor productivity (TFP) into technical progress and efficiency improvement. This decomposition is not only helpful in discovering the relative importance of sources of economy growth, but is also suitable to depict the Chinese reality of production and economic growth.

Traditional DEA models, such as those employed by Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984), have assumed a convex production possibility set or a concave production frontier. This means that they apply production technology that inherently yields diminishing returns to scale. In order to relax the convexity assumption of the production frontier, Petersen (1990) substituted a convex input requirement set (IRS) and a convex production possibility set (OPS) for the convex production possibility set assumptions to form a *quasi*-concave production frontier. Deprins, Simar, and Tulkens (1984) also proposed the free disposal hull (FDH) method. There is also a history of scholars applying DEA to Chinese agricultural productivity. Mao and Koo (1997) analyze total factor productivity, technology, and efficiency changes in Chinese agricultural production from 1984 to 1993. They show that total factor productivity rose in most provinces during that period. Technical progress contributed the most to Chinese agricultural productivity growth after the rural economic reforms. Meanwhile, efficiency changes contributed little to the growth of China's agricultural productivity. Due to the poor performance of technical efficiency in many important agricultural provinces, Mao and Koo suggest that there is a great potential for China to increase agricultural productivity through improved technical efficiency. Chen (2006) investigated agricultural TFP and its distribution over time and space, and showed that annual average growth of agricultural productivity in China was about 2.6 percent from 1990 to 2003. Technological progress improved agricultural productivity at an average rate of 5.5 percent annually but the technology efficiency dampened it by an average of 2.8 percent per year. But these studies are flawed in that the data employed do not reflect the full array of dynamic changes undertaken by Chinese agricultural productivity from the initial stage of reform to China's entry into the World Trade Organization (WTO). Li

[3]Although Chinese farmers now have incentive to improve their technical efficiency, due to historical factors farm labor remains quite redundant. Hence, due to the relative scarcity of machinery, technical inefficiency in farming is quite prevalent, especially in Central and West China.

and Meng (2006) also employed this method and expanded the range of data from 1978 to 2004. But they encountered a problem when matching input and output data in their calculations, which undoubtedly led to biased conclusions.

The convergence hypothesis, which implies that an economy whose productivity lags behind other economies has a potential to grow faster than the average, has become a heavily debated economic issue. The major theories providing a rationale for the convergence hypothesis include technology transfer and the neoclassical growth model. According to the technology transfer argument, the flow of technology should provide an opportunity for less advanced economies to advance rapidly toward economic conditions experienced in more advanced nations (Elmslie 1995). This argument rests on the idea that it is less costly for less advanced economies to imitate than to innovate. The prerequisites for successful imitation and rapid growth include, for the most part, an adequate pool of technical and managerial skills, as well as stable political and financial institutions and public policies conducive to productive entrepreneurial activities (Rassekh, Panik, and Kolluri, 2001).

The neoclassical growth model predicts that every economy approaches its own steady-state income determined by exogenous forces including saving and population growth rates. And because of diminishing returns to reproducible capital, an economy with a lower capital/labor ratio relative to another economy has a higher marginal productivity of capital and an opportunity to grow faster.

Following the pioneering work of Baumol (1986) and Abramovitz (1986), considerable efforts have been devoted to investigating the pattern of convergence in different national and regional samples. Barro and Sala-i-Martin (2003) identify two main concepts to estimate convergence among different economic units—σ-convergence and β-convergence. A group of economies exhibits σ- convergence if the dispersion of per capita income tends to decline over time. On the other hand, β-convergence exists in a cross-section of economies, if poor economies tend to grow faster than wealthy ones. β-convergence can be further divided into β-conditional convergence and β-absolute convergence. If two economies have relatively similar technological, preference, and demographic endowments, their steady-state levels of capital and output per capita will be approximately the same. In this case, all economies converge to the same steady state and the poorest economies should grow faster than the richest ones—this is called β-absolute convergence. In the real world, however, there exists a great variety between countries with regard to factors relevant to growth such as their levels of technology, their propensities to save, and their population growth rates. This implies that each country may have its own steady level of growth, and that the growth rate of an economy will be positively related to the distance that separates it from its own steady state. This is the concept of β-conditional convergence, which focuses upon the relationship between the growth rate of income and the initial income endowment.

Despite a general interest in the convergence of provincial income per capita across China, literature on the convergence of agriculture productivity among China's provinces has been scant. What is more, the few pieces that exist do not come to very robust conclusions. Zhao, Yang, and Wang (2007) implemented a convergence test of 28 provinces in China from 1980 to 2003 using the panel unit root test and found no σ-convergence in Chinese agricultural productivity. But he did find absolute and conditional β-convergence across China, with speeds of 3.2 percent and 5.2 percent, respectively. Han and Zhai (2005) posited that there has been conditional convergence in rural areas since 1992 and that different speeds of economic and social development among the provinces were the root cause of agriculture productivity differences among coastal, central, and western China.

DEA is unique in its ability to appraise efficiency in the context of multiple inputs and outputs. (Thus, DEA also can be used to measure the relative efficiency among different decision-making units for the more conventional situation of multiple inputs and a single output.) This article uses DEA to analyze the agriculture productivity of 29 Chinese provinces and cities from 1980 to 2005 and to test productivity convergence. In estimating productivity, we expand Chen's (2006) data scope backward to 1980 in the hope that it will help us get a grasp of the evolutionary dynamic of agricultural productivity since the period of reform and up through China entry into the WTO. This paper also distinguishes itself from Li and Meng (2006) in that it unifies the data detail of inputs and outputs and also matches the two sets of data. As a result, the findings should lead to much more robust conclusions.

3. METHOD AND DATA

3.1 Estimation Approach

DEA applies mathematical programming to appraise the relative efficiency of decision-making units (DMU). It yields an optimal production frontier that depends on the structure of the existing data and defines the relative efficiency change by computing distances from the efficiency frontier for the entire data sample in two phases—those output-oriented and those input-oriented. Because land and other inputs in agriculture change little in the long run, in contrast to drastic fluctuations of output, input-oriented DEA models are used, i.e. models that maximize output with respect to an input set.

Applying Färe et al. (1994), we suppose a production frontier of $t=1,...,T$ in each period that can be described as follows:

$$S^t = \left\{ (x^t, y^t):\ \text{x}^\text{t} \text{ can produce y}^\text{t} \right\} \quad (1)$$

where x^t is the input vector, y^t the output vector, and S^t is the level of technology. The output distance between the observation t and the production frontier can be defined as follows:

$$D_0{}^t(x^t, y^t) = \inf\left\{\theta : (x^t, y^t/\theta) \in S^t\right\} = \left(\sup\left\{\theta : (x^t, \theta y^t) \in S^t\right\}\right)^{-1} \quad (2)$$

Färe et al. note that the ratio of output distance in two different periods is a Malmquist index. The Malmquist index for the reference technology in time t and that in time $t+1$ is:

$$M^t_{CCD} = \frac{D_0{}^t(x^{t+1}, y^{t+1})}{D_0{}^t(x^t, y^t)} \quad \text{and} \quad M^t_{CCD} = \frac{D_0{}^{t+1}(x^{t+1}, y^{t+1})}{D_0{}^{t+1}(x^t, y^t)}$$

Here, the distance function $D_0{}^t(x^{t+1}, y^{t+1})$ measures the maximal proportional change in output required to make (x^{t+1}, y^{t+1}) feasible in the technology at t. Similarly, $D_0{}^{t+1}(x^t, y^t)$ measures the maximal proportional change in output required to make (x^t, y^t) feasible in relation to the technology at $t+1$. To avoid choosing an arbitrary benchmark, Färe et al. use the geometric mean of M_{CCD}^{t} and M_{CCD}^{t+1} to derive the Malmquist productivity index so:

$$(3)\qquad M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_0^{\,t}(x^{t+1}, y^{t+1})}{D_0^{\,t}(x^t, y^t)}\right)\left(\frac{D_0^{\,t+1}(x^{t+1}, y^{t+1})}{D_0^{\,t}(x^t, y^t)}\right)\right]^{\frac{1}{2}}$$

Or equivalently

$$(4)\qquad M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{\,t+1}(x^{t+1}, y^{t+1})}{D_0^{\,t}(x^t, y^t)} \times \left[\left(\frac{D_0^{\,t}(x^{t+1}, y^{t+1})}{D_0^{\,t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_0^{\,t}(x^t, y^t)}{D_0^{\,t+1}(x^t, y^t)}\right)\right]^{1/2}$$

where the first term estimates the output-oriented relative technical efficiency change (TEC) between t and $t+1$ and shows the "catch-up effect" of the observation sample with respect to the production frontier. The second term—the geometric average—pertains to technical change, i.e. technical progress. Therefore, Equation (4) represents total factors production change (TFPC) as follows:

$$(5)\qquad TFPC = TEC \times TC$$

The decomposition of TFP into technical catch-up and technical progress is new to the study of the neo-classical convergence hypothesis. Nevertheless in Equation (4) the Malmquist index assumes constant returns to scale. In order to tease out the influence of technology efficiency from possible variable returns to scale, Estace, Tovar de la Fé, and Trujillo（2004）add the distance function for output in the case of variable returns to scale to Equation (4), so that relative TEC can be further categorized into pure technical efficiency change (PTEC) and scale efficiency change (SEC).

(6)

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{\,V,t+1}(x^{t+1}, y^{t+1})}{D_0^{\,V,t}(x^t, y^t)}\left[\left(\frac{D_0^{\,V,t}(x^t, y^t)}{D_0^{\,V,t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_0^{\,C,t+1}(x^{t+1}, y^{t+1})}{D_0^{\,C,t}(x^t, y^t)}\right)\right]$$
$$\times\left[\left(\frac{D_0^{\,C,t}(x^{t+1}, y^{t+1})}{D_0^{\,C,t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D_0^{\,C,t}(x^t, y^t)}{D_0^{\,C,t+1}(x^t, y^t)}\right)\right]^{1/2}$$

Here, the superscripts V and C denote variable and constant returns to scale, respectively. The first term is PTEC, the second is SEC, and the last is the same as Equation (5), which is TC. Alternatively in short-hand form:

$$(7)\qquad TFPC = PTEC \times SEC \times TC$$

To solve (7), six linear programs are needed: four constant returns to scale (that is $D_0^{C,t+1}(x^{t+1}, y^{t+1})$, $D_0^{C,t}(x^t, y^t)$, $D_0^{C,t}(x^{t+1}, y^{t+1})$ and $D_0^{C,t+1}(x^t, y^t)$) and two variable returns to scale (that is $D_0^{V,t}(x^t, y^t)$ and $D_0^{V,t+1}(x^{t+1}, y^{t+1})$). We suppose there are $k = 1,\ldots,K$ regions using $n = 1,\ldots,N$ inputs $x_n^{k,t}$ at each period of time $t = 1,\ldots,T$ .These inputs are used to produce

$m=1,\ldots,M$ outputs $y_m^{k,t}$.In our data, each observation of inputs and outputs is strictly positive. $D_0^{C,t}(x^t, y^t)$ in region k' can be achieved by the solution of linear programming model in formula (8):

(8) $$\left[D_0^{C,t}(x^{k',t}, y^{k',t})\right]^{-1} = \max \theta^{k'}$$

$$\theta^{k'} y_m^{k',t} \le \sum_{k=1}^{K} z^{k,t} y_m^{k,t} \qquad m=1,\ldots,M$$

$$\sum_{k=1}^{K} z^{k,t} x_n^{k,t} \le x_n^{k',t} \qquad n=1,\ldots,N$$

$$z^{k,t} \ge 0 \qquad k=1,\ldots,K$$

where $z^{k,t}$ is a variable indicating the intensity of a particular activity (in our case, each region has but one activity) employed in production, θ is scalar, $1/\theta$ is the technical efficiency of the samples. The computation of $D_0^{C,t+1}(x^{k',t+1}, y^{k',t+1})$ is exactly like (8), where $t+1$ is substituted for t. Likewise, to count variable returns to scale $D_0^{V,t}(x^{k',t}, y^{k',t})$ and $D_0^{V,t+1}(x^{k',t+1}, y^{k',t+1})$ separately require adding the constraint $\sum_{k=1}^{K} z^{k,t} = 1$（Färe et al.，1994）to Equation (8). The two distance functions used to construct the Malmquist index require information for two periods. The first of these is computed for observation k' as:

(9) $$\left[D_0^{C,t}(x^{k',t+1}, y^{k',t+1})\right]^{-1} = \max \theta^{k'}$$

$$\theta^{k'} y_m^{k',t+1} \le \sum_{k=1}^{K} z^{k,t} y_m^{k,t} \qquad m=1,\ldots,M$$

$$\sum_{k=1}^{K} z^{k,t} x_n^{k,t} \le x_n^{k',t+1} \qquad n=1,\ldots,N$$

$$z^{k,t} \ge 0 \qquad k=1,\ldots,K$$

Another mixed-period Malmquist index $D_0^{C,t+1}(x^{k',t}, y^{k',t})$ is specified as (9), but with the time indicators transposed. TFPC in formula (7) is obtained by the solution to the above linear programming models.[4]

[4] This paper covers 26 years of data for 28 provinces and cities (the data of Hainan and Chongqing are merged into those of Guangdong and Sichuan Provinces, respectively.). This results in 728 observations, so that 2,856 linear programming models must be computed.

3.2 Data

This study uses agriculture input and output data for 30 provinces, autonomous regions, and municipalities operating directly under the Central Government for the mainland of China for the 1980-2005 period. Because Hainan Province and the Chongqing city were separated from other provinces during the study period, we merged data for Hainan Province into Guangdong Province and that for Chongqing city into Sichuan Province. Moreover, by virtue of its mountainous terrain there is a large agriculture productivity gap between the Tibet Autonomous Region and the rest of China: hence, it is not included in our analysis. All the data come from *50 Years Agricultural Statistical Material of New China*, *China Statistical Yearbook* (various years), and the *Chinese Countryside Statistical Yearbook* (various years).

Output data come from the total agricultural output value, which is expressed in constant 1990 prices.[5] Here special attention should be paid since there are two kinds of total rural output value in various areas in constant prices in earlier statistical yearbooks: that for 1990-2005 is in constant 1990 prices and that for 1980-1990 is in constant 1980 prices. Using output from 1990 measured in both current and constant 1980 prices, we transformed the output value in constant 1980 prices to constant 1990 prices.

This test takes four indexes as inputs. They consist of labor force in farming, forestry, animal husbandry, side-occupations and fishing, quantity of chemical fertilizers (tons), total power output of farm machinery (ten thousands of kilowatts per year), and sown area.

4. EMPIRICAL RESULTS

DEAP is used to measure the annual provincial change in TFP.[6] According to the fluctuation of the growth rate of the total agricultural output value, we divide our analysis of the agricultural productivity into four phases: 1980-1985, 1986-1989, 1990-1995, and 1996-2005. We also analyze by region: eastern, central and western China.[7]

4.1 Total Factor Productivity (TFP) and the Growth Rate of Total Rural Output Value

According to Table 1, TFP grew at an annual average rate of 2.2 percent from 1980 to 2005, during which the technical innovation rate's contribution was 4.2 percent, while the relative technical efficiency's had actually declined by an annual average of 1.9 percent. Li and Meng (2006) came to a more consistent set of conclusions for the growth rate of TFP, since they found the technical innovation rate and technical efficiency had the same directional effect on TFP but with somewhat different magnitudes, which may have been caused by their use of the incompatible data that was discussed earlier.

The Chinese agricultural technology advancement rate for the period 1980-2005 was generally above 4 percent, with the exception being the 1985-1986 interval, when it was only about 0.3 percent. The relative technical efficiency was improved only slightly (an average of 0.2 percent) in the initial period of reform (namely, 1980-1985). Additionally, note that the scale of agricultural production income does not vary much from 1980 to 1985, although since 1985 it

[5] Here, total agricultural output includes the gross output of farming, forestry, animal husbandry, and fishery.

[6] DEAP is a computer program which has been written to conduct data envelopment analyses (DEA) for the purpose of calculating efficiencies in production. More detail can be arrived in Coelli (1996).

[7] Eastern China covers Liaoning, Beijing, Tianjin, Shanghai, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan; Central China includes Heilongjiang, Jinlin, Shanxi, Inner Mongolian, Anhui, Jiangxi, Henan, Hubei and Hunan; Western China refers to Chongqing, Sichuan, Yunnan, Guizhou, Shaanxi, Qinhai, Gansu, Ningxia, Xinjiang, and Guangxi.

TABLE 1. Change of Previous Average TFP Index and Its Decomposition*

Year	TEC	TC	PTEC	SEC	TFPC
1980-1981	1.091	0.937	1.076	1.014	1.022
1981-1982	0.966	1.118	0.976	0.990	1.08
1982-1983	1.025	0.983	1.017	1.008	1.008
1983-1984	0.995	1.088	0.997	0.998	1.083
1984-1985	0.930	1.120	0.941	0.989	1.042
Mean 1980-1985	1.0018	1.0496	1.002	1.000	1.047
1985-1986	0.983	0.987	0.989	0.994	0.971
1986-1987	0.977	1.034	0.981	0.996	1.01
1987-1988	0.996	0.993	0.998	0.998	0.989
1988-1989	0.963	0.999	0.987	0.976	0.962
Mean 1985-1989	0.98	1.003	0.989	0.991	0.983
1989-1990	0.985	1.038	0.98	1.005	1.022
1990-1991	1.013	1.033	1.009	1.004	1.046
1991-1992	0.966	1.065	0.987	0.979	1.029
1992-1993	1.011	1.019	0.996	1.015	1.03
1993-1994	0.959	1.032	0.989	0.970	0.989
1994-1995	0.981	1.088	0.996	0.985	1.067
Mean 1989-1990	0.986	1.046	0.993	0.993	1.031
1995-1996	0.944	1.091	0.976	0.967	1.03
1996-1997	0.920	1.089	0.946	0.972	1.001
1997-1998	1.00	0.995	0.997	1.003	0.995
1998-1999	1.075	0.933	1.00	1.075	1.004
1999-2000	0.948	1.090	0.986	0.962	1.033
2000-2001	0.951	1.079	0.98	0.971	1.027
2001-2002	0.899	1.154	0.982	0.916	1.037
2002-2003	0.911	1.152	1.012	0.900	1.049
2003-2004	1.029	1.001	1.012	0.900	1.049
2004-2005	1.045	0.970	1.001	1.043	1.014
Mean 1995-2005	0.972	1.055	0.989	0.983	1.022
Overall Mean	0.981	1.042	0.992	0.989	1.022

Note: According to Färe et al. (1994), an index value greater than 1.0 indicates positive growth and less than 1.0, negative growth. Rate of increment was equal to the index subtract

* Lack of space forbids details for previous years of the Malmquist index and regional decompositions, which are available upon request.

has decreased gradually. This further supports the notion that productivity growth continues to be extremely important to agriculture in China.

Comparing the tendencies of the agricultural productivity and the growth rate of total agricultural output reveals that they are fairly parallel from 1980 to 1996, but subsequently diverge after 1996 (see Figure 1). A simple correlation of TFP and rural output reveals that TFP explains 53.3 percent (1980-1985), 92.3 percent (1986-1989), 0.4 percent (1990-1995) and 16.5

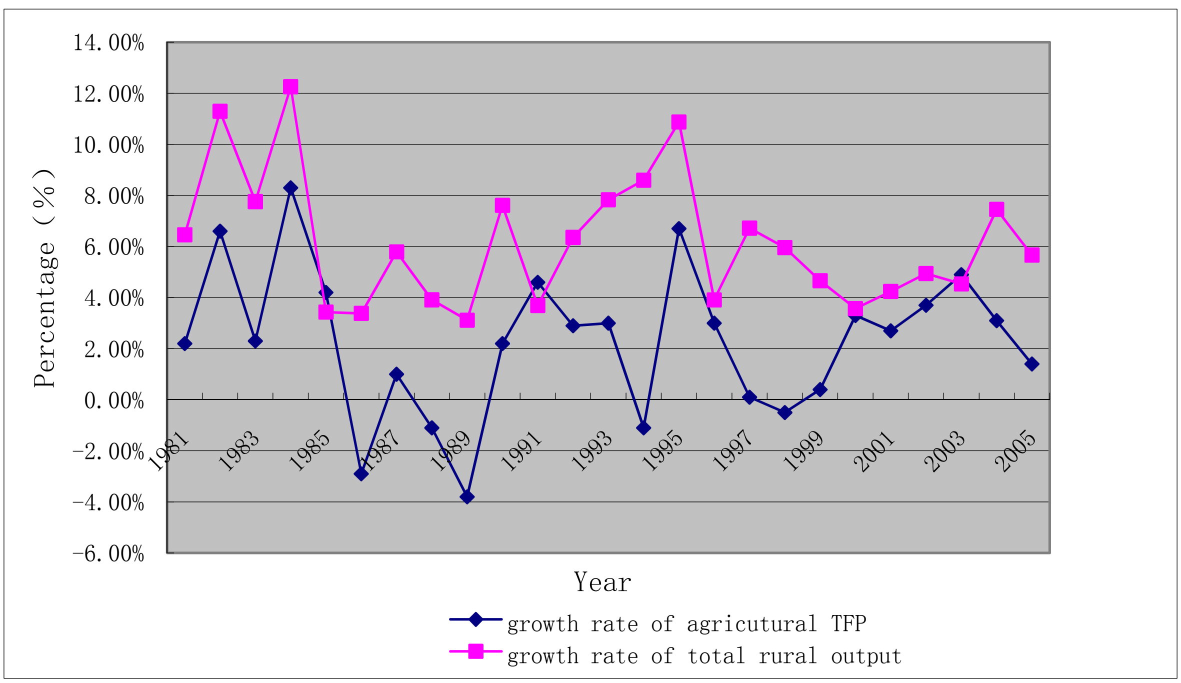
percent (1996-2005) of the variance in agricultural output for each respective period. These numbers indicate that in the initial period of reform (1980-1985), high growth of agriculture in China mainly originated from advances in agricultural productivity due to institutional reforms; similar conclusions have been obtained by McMillan, Whalley, and Zhu (1989); Lin (1992); and Wen (1993). While the decline in growth rate between 1986 and 1989 was caused by a drop in agricultural TFP, after 1990 agriculture productivity edged up only slightly, particularly through 1995.

4.2 Comparative Analysis of Agricultural TFP in East, Central, West China

Table 2 shows evidence that China's agricultural productivity change is characterized by regions. In this paper, the nonparametric Kruskal-Wallis test and the median test are performed first to identify differences in the TFPC of East, Central and West China, as shown in Tables 3 and 4.

The Kruskal-Wallis test in Table 3 shows that the mean ranks of the different samples are, respectively, 49.3, 33.7, and 30.6. Accordingly, in the east, central, and west regions the concomitant statistical significance of the test is 0.005, which means the TFPC in the three regions are statistically different from one another. The median test in Table 4 reveals the best common median for the three regions would be 1.0229. Nonetheless that the probability of the three regions sharing this median is 0.005, which suggests that agricultural productivity change in the three regions is quite different. Thus, the two tests agree that there are notable differences in the progress rate of agricultural TFP across Central, West, and East China.

FIGURE 1. Growth Rate of Agricultural TFP and Total Agricultural Output Value, 1980-2005



Source: Growth rate of total rural output value is computed in light of *China's Agriculture Statistical Yearbook* (2006) and new China's 50-year Statistical Material Collection. Data for TFP growth rate are in Table 1.

TABLE 2. Change of TFP in East, Central and West China, 1980-2005

	East			Central			West		
	TEC	TC	TFPC	TEC	TC	TFPC	TEC	TC	TFPC
1980-1981	1.0853	0.9907	0.9907	1.1369	0.9079	1.0312	1.0543	0.9693	1.0202
1981-1982	0.9680	1.1503	1.1137	0.9222	1.1103	1.0229	0.9799	1.1166	1.0957
1982-1983	1.0218	1.0104	1.0321	1.0248	0.9825	1.0063	1.0742	0.9548	1.0268
1983-1984	0.9859	1.1053	0.9916	1.0069	1.0652	1.0721	0.9814	1.0682	1.0485
1984-1985	1.0694	1.1446	1.0694	0.8959	1.1292	1.0108	0.9450	1.0640	1.0041
1985-1986	0.9795	1.0154	0.9942	0.9762	0.9743	0.9501	1.0098	0.9474	0.9569
1986-1987	0.9768	1.0487	1.0244	1.0064	1.0298	1.0353	0.9847	1.0002	0.9846
1987-1988	1.0012	1.0138	1.0153	0.9506	0.9866	0.9378	1.0142	0.9650	0.9787
1988-1989	0.9685	1.0069	0.9752	0.9832	0.9853	0.9679	0.9858	0.9829	0.9687
1989-1990	0.9940	1.0467	1.0404	0.9911	1.0392	1.0301	0.9734	1.0170	0.9893
1990-1991	1.0527	1.0339	1.0858	0.9985	1.0105	1.0090	1.0237	1.0472	1.0711
1991-1992	0.9648	1.0794	1.0394	0.9959	1.0547	1.0468	0.9605	1.0548	1.0100
1992-1993	1.0364	1.0214	1.0579	1.0058	1.0206	1.0265	0.9974	1.0052	1.0025
1993-1994	0.9894	1.0385	1.0269	0.9574	1.0253	0.9819	0.9612	0.9980	0.9582
1994-1995	1.0359	1.1142	1.1534	0.9816	1.1283	1.1069	0.9489	1.1079	1.0509
1995-1996	0.9963	1.0654	1.0583	0.9733	1.0732	1.0426	0.8587	1.0642	0.9135
1996-1997	0.9499	1.0898	1.0348	0.9216	1.0855	0.9991	0.9214	1.0830	0.9967
1997-1998	1.0123	1.0096	1.0206	0.9516	1.0143	0.9623	0.9473	1.0190	0.9615
1998-1999	1.0669	0.9914	1.0524	1.0904	0.9442	1.0199	1.0183	0.9748	0.9837
1999-2000	0.9483	1.1045	1.0460	0.9466	1.0750	1.0171	0.9415	1.0732	1.0096
2000-2001	0.9341	1.1160	1.0405	0.9555	1.0540	1.0049	0.9868	1.0221	1.0076
2001-2002	0.9130	1.1407	1.0402	0.8754	1.1548	1.0106	0.8913	1.1613	1.0347
2002-2003	0.9194	1.1558	1.0622	0.8767	1.1511	1.0093	0.9185	1.1490	1.0554
2003-2004	1.0525	0.9998	1.0524	1.0312	1.0018	1.0330	1.0324	0.9959	1.0280
2004-2005	1.0555	0.9749	1.0288	1.0444	0.9689	1.0118	1.0732	0.9577	1.0276
1st Year Mean	0.9991	1.0587	1.0419	0.9800	1.0389	1.0138	0.9794	1.0319	1.0074
Std Deviation	0.0490	0.0570	0.0380	0.0600	0.0650	0.0360	0.0530	0.0600	0.0400

Note: Data are calculated using weighted averages.

TABLE 3. Kruskal-Wallis Test of TFPC by Region

Areas	*N*	Mean Rank
East	25	49.72
Central	25	33.72
West	25	30.56
Total	75	

	Test Statistics
Chi-square	11.107
df	2
Asymptotic Significance	.004

TABLE 4. Test of TFPC's Difference from the Median Value

Frequencies	Areas		
	East	Central	West
TFPC > Median	19	9	9
<= Median	6	16	16

Test Statistics	TFPC
N	75
Median	1.022900
Chi-Square	10.669
df	2
Asymptotic significance	.005

As far as TFP growth is concerned, average annual growth in the East is 4.2 percent, in the Central region 1.4 percent, with the West being slowest at 0.7 percent. Similarly, technology change is fastest in East China, where it is 5.9 percent, less rapid in Central China at 3.9 percent, and the West's annual rate of advance is slowest at 3.2 percent. With regard to technical efficiency, there is little if any change in the East, but it declines in the West and Central China. For provinces and municipalities, the quickest growth of TFP took place in Beijing, Shanghai, Jiangsu, Fujian, Liaoning, Shandong, and Guangdong. It is a little slower in the western provinces, among which there are two provinces with negative growth rates—Inner Mongolia autonomous region and Guizhou province. As for variation in TFP growth, it was greater in the West (standard deviation of 0.04), than in the East, and the least variable in Central China. Fluctuation in technological innovation is the most evident in Central China and the least in the East. This reflects the long-term power of technological innovation along China's coast.

3.3 Inducement of TFP growth

Data in Table 2 and Table 3 show that technology change in China is the main impetus for agricultural TFP growth. Agricultural technology change more than counteracts the negative influence of degrading agriculture efficiency and even promotes TFP growth. The research of Chen (2006), Li and Meng (2006) concludes similarly.

Figure 2 displays the accumulated growth rate of agricultural TFP, technology change and technical efficiency from 1980 to 2005. In particular it reveals the cumulative growth rate of TFP was 0.572 and of technical change 1.09, while technical efficiency was -0.435 (see Table 4). Between 1980 and 1985 technical efficiency improved somewhat, but after 1986 it gradually declined (i.e. the distance to China's frontier technology widened). This suggests that worsening technology efficiency was the main reason technical progress did not fully transform into TFP growth.

Table 5 shows that there is a great difference in cumulating technology efficiency, technical progress and growth rate of TFP across China's main regions, which derives from distinct regional characteristics. The cumulative growth rate of TFP in the East is higher than that in Central China by far, and the TFP of the latter is higher than that in the West. Technology efficiency declines least in the East, but is a serious concern in the Central and Western regions; accumulative technology advancement rate in the East is also much higher than that in the Central and Western areas.

5. TESTING FOR AGRICULTURAL PRODUCTIVITY CONVERGENCE

There are great differences in TFP, technology change, and technology efficiency across China's East, Central, and West regions. But how has this regional disparity developed and evolved? To answer this, we test the convergence of TFP in the three areas.

FIGURE 2. Cumulative Growth Rate of Agricultural TFP, Technical Progress and Technology Efficiency, 1980-2006

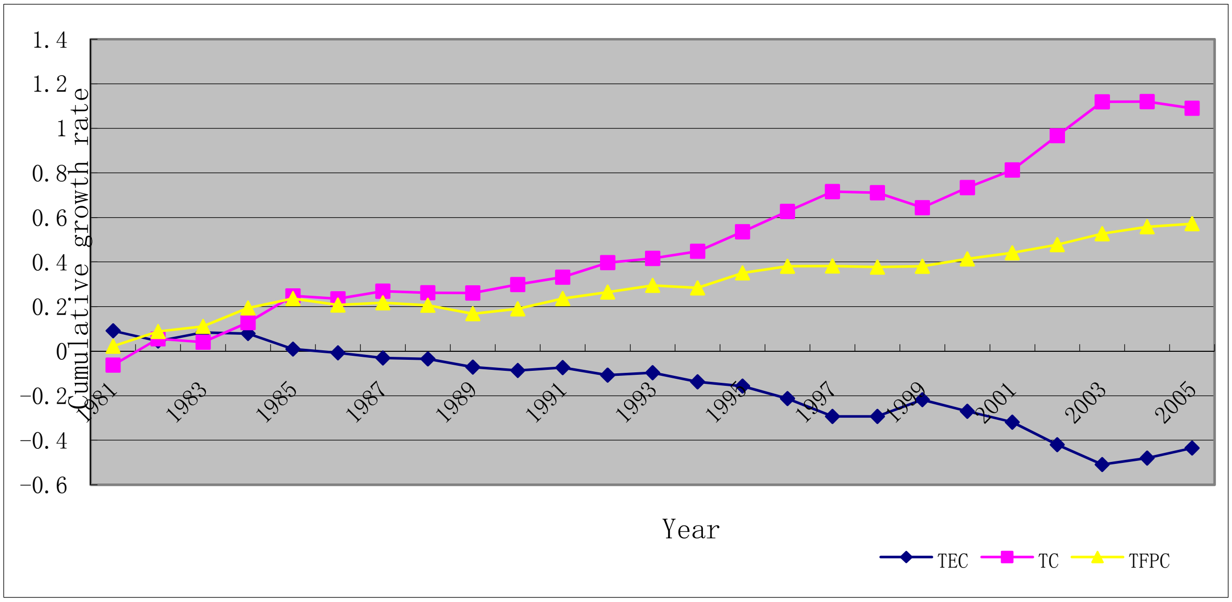


TABLE 5. Cumulative Growth Rate of Technology Efficiency, Technology Change, and TFP

	Efficiency	Technology	TFP
East	-0.0221	1.4680	1.5219
Central	-0.4997	0.9726	0.3461
West	-0.5161	0.7987	0.1845
Nation	-0.435	1.090	0.572

Source: Table 2

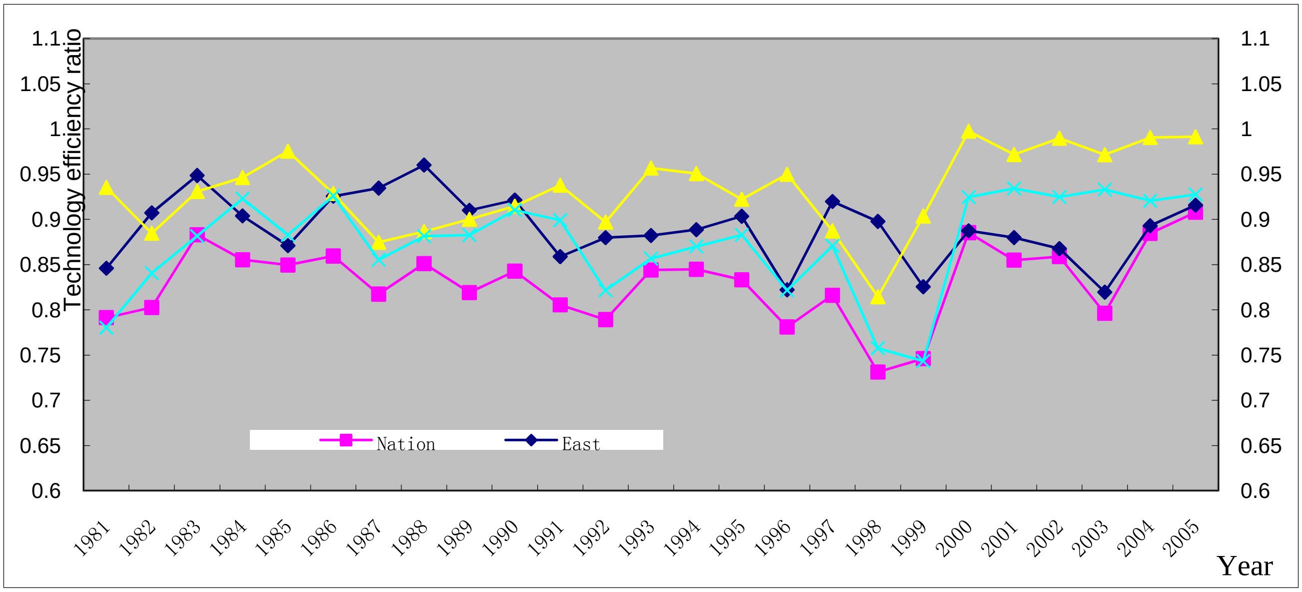
5.1 Judging Convergence in Terns of Relative Technology Efficiency

Technology efficiency decomposed by means of the Malmquist index represents the average distance from all observations in the sample analyzed to the sample's production frontier. Thus, the greater the distance, the larger the gap between the sample average and the region's most advanced technology for the period. Therefore, the dynamic evolution of relative technical efficiency can give us some insight into the nature of productivity convergence.

Figure 3 compares the ratio between the average value of the five lowest provinces (and municipalities) in terms of technology efficiency to the average value of five highest provinces in technical efficiency; both of the nation as a whole as well as for each of the three broad regions of China.[8] Obviously, the lower the ratio, the broader the productivity gap. According to Figure 3,

[8] National data is the ratio of the five lowest samples' relative technology efficiency average value and that of the five highest

FIGURE 3. Technology Efficiency Ratio, 1981-2005



the national data show four basic stages where the ratio of relative technology efficiency increases: 1981-1983, 1992-1995, 1998-2000, and 2003-2005. It reveals a tendency toward convergence during these periods, but divergence trends in the other periods. From the perspective of the three different regions, neither convergence nor divergence is obvious in the East, while divergence was apparent from 1996 to 1998 from the perspective of the Central region, with a convergence tendency from 1984 to 1999. For the West, convergence was observed from 1981 to 1984 and 1999 to 2000, but divergence was the trend in the interim period. All of this proves that there was no general trend for convergence and divergence across regions during any specific period.

5.2 Testing for σ-convergence

According to Barro and Sala-I-Martin (2003), the literature records two main mechanisms to estimate convergence among different economic units—σ- convergence and β-convergence. The concept of σ convergence occurs if the variance of per capita income declines across a group of countries or regions over time. The concept of β—convergence can be further divided into β-conditional convergence and β-absolute convergence. It describes the relationship between the growth rate of per capita income based on the initial endowment of per capita income. Recent literature testing for the convergence hypothesis concentrates on β-convergence (Liu, Wei, and Li 2004). Traditional "Barro regressions" that test for β-convergence turn out to be plagued by Galton's fallacy of regression toward the mean (Friedman 1992; Quah 1993). Also, Bernard and Durlauf (1995, 1996), Durlauf and Johnson (1995), and Evans and Karras (1996a, 1996b) are doubtful about test results for β-convergence. Thus Friedman (1992) and Quah (1993) suggest strictly analyzing σ- convergence. So, we mainly focus upon σ -convergence of agricultural productivity across the regions, where σ is defined as:

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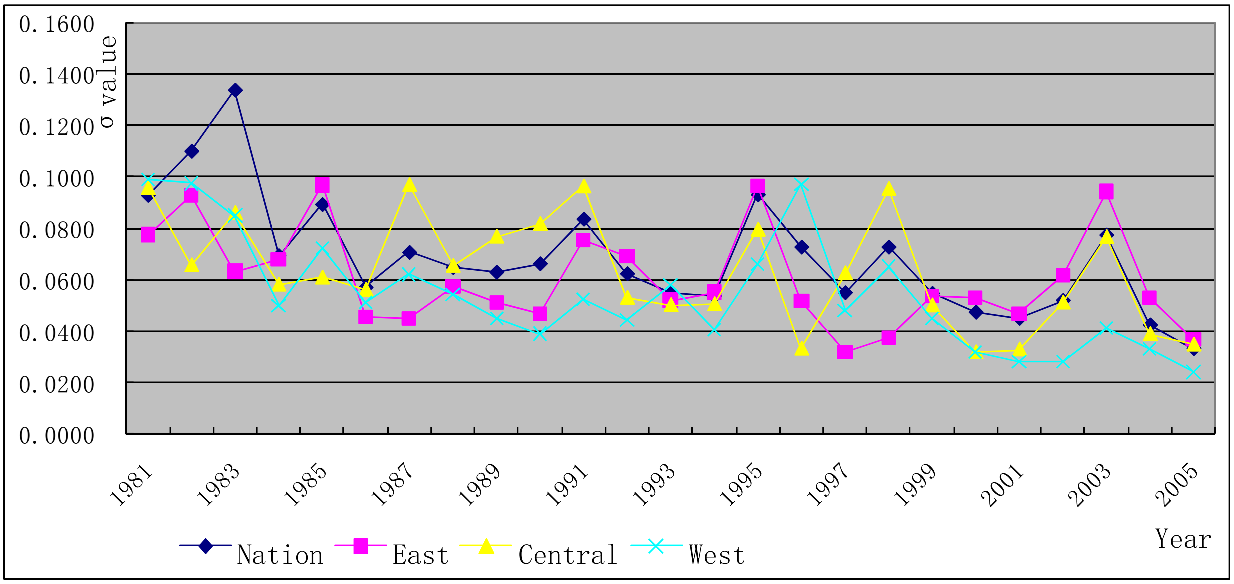
samples for the pertinent year, and regional data comes from the ratio of the three lowest average values and that of the three highest from diverse regions.

FIGURE 4. σ-Convergence in Agricultural Productivity, 1981-2006



$$\sigma_t = \left\{ N^{-1} \sum_{m=1}^{N} \left[TFP_m(t) - \left(N^{-1} \sum_{k=1}^{N} TFP_k(t) \right) \right]^2 \right\}^{1/2} \tag{10}$$

Here, $TFP_m(t)$ signifies productivity of district m in time t. If $\sigma_{t+T} < \sigma_t$, there exists σ-convergence of agricultural productivity across China.

Figure 4 shows σ value change across the nation as well as within its three major regions. It is obvious that the value of σ is in a reduction state whether in the national data or the regional data, so as a whole a convergence tendency exists in China's agricultural productivity. As in Figure 3, it also has the different reflections in different regions in the different intervals.

6. CONCLUSIONS

According to above analysis, we can draw five conclusions:

1) The annual average growth rate of TFP in China was 2.2 percent between 1980 and 2005, with technology change increasing by 4.2 percent and relative technical efficiency declining by 1.9 percent yearly;

2) Agricultural productivity change explains agricultural production change from 1980 to 1989, but after 1990 the agricultural production was influenced by factors other than productivity;

3) For regions, the growth rate of TFP and technology change in East China is higher than in Central China, but the growth rate in Central China was higher than the ratein the West. For technical efficiency, there is little change in the East, but it declines in Central and West China, albeit by different degrees;

4) The main impetus for agricultural productivity growth in China has been its technology change;

5) As a whole, σ-convergence tendency exists in China's agricultural productivity during the period 1980 to 2005.

Some recommendations can be derived from the above conclusions First, China's government should continue to increase its subsidy for agricultural technology to generate greater growth in agricultural productivity. We come to this conclusion because it is clear from our evidence and those of others that technological progress promotes agricultural productivity in China and that the farm economy causes rural China to lag severely behind its urban counterpart, at least from an income perspective. Second, we believe that the technology exchange and cooperation as well as diffusion of know-how should be encouraged among the various regions of China. This will also help to reduce rural-urban income disparities induced by the deterioration of agricultural technological efficiency in Eastern and Central regions of the country. Although we focused in this paper on change in agricultural productivity, we did not consider factors that influence production change more generally. Hence, further study is needed for this comprehensive and critical topic.

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