Productivity Growth and Its Components in Chinese Agriculture After Reforms

AERS 98 - 3

Shunxiang Wu, David J. Walker, and Stephen Devadoss

March 4, 1998

Productivity Growth and Its Components in Chinese Agriculture After Reforms

by

Shunxiang Wu, David J. Walker, and Stephen Devadoss*

Abstract

This study uses nonparametric Malmquist procedures to investigate the temporal and spacial nature of productivity growth and its components in Chinese agriculture over the period 1980-1995. The results of this study indicate that total factor productivity grew at 2.37% annually with technical change augmenting the growth by 3.76% while efficiency change reducing productivity growth by 1.44%. For all provinces and time periods, 288 out of a total of 442 cases experienced productivity growth while the rest showed productivity regression during this post-reform period. Coexistence of amelioration in technical change and retardation in efficiency change indicates the lack of success in diffusing the existing agricultural technology. Continuing innovation and efficiency improvement through capital investment, modern input use, and greater competitive market pressures are important for augmenting productivity growth in Chinese agriculture.

Keywords: Chinese agriculture, economic reform, Malmquist productivity change index, and nonparametric programming approach

---

*Shunxiang Wu, David J. Walker, and Stephen Devadoss are, respectively, research fellow, professor, and associate professor in the Department of Agricultural Economics and Rural Sociology at the University of Idaho, Moscow.

Productivity Growth and Its Components in Chinese Agriculture After Reforms

China initiated agricultural reforms in the late 1970s as part of its economic transition programs by decentralizing farm production decisions to family units. These reforms resulted in remarkable progress in the Chinese agricultural sector. Grain production grew at an average rate of about 3% annually during 1978-95. In 1996, grain production reached a record of 490 million tons (USDA). After two decades of progress, China has developed the capability to provide the basic food needs for 22% of the world population with only 7% of the world's arable land. Many have attributed this high growth in agricultural productivity to research, technical innovation, institutional reforms, free-market oriented policies, and industrial growth (McMillan, Whalley, and Zhu; Ma, Calkins, and Johnson; Fan; Fan and Pardey; Fleisher and Liu; Lin, 1987, 1992; Wang, Cramer, and Wailes; Kalirajan, Obwona, and Zhao; Koo and Duncan).

Lin (1987) reported that a shift from the cooperative production system to the household farming system resulted in a 20% increase in agricultural productivity during 1980-83. Using provincial-level data and a growth accounting approach, Fan found that total factor productivity (TFP) in agriculture grew at an average rate of 2.13% per year during 1965-86; 62% of this growth was attributed to efficiency improvement from institutional change, while the remaining 38% was imputed to technical progress. Fan and Pardey estimated that investment in agricultural research accounted for 20% of productivity growth for the nation during 1965-89; however, advancement in research contributed to productivity growth unequally among regions (e.g., 35% in Southeast and 8.6% in North).

Using provincial-level data, Lin (1992) found that all reform measures combined accounted for 42% of the growth in agricultural output during 1978-84. He also concluded that about 46% of this reform-induced output growth came from the increased input use (mainly chemical fertilizer) and 49% from efficiency improvement. A more recent study by Lin (1995) indicated that removal of legal restrictions on factor markets in China has contributed to the efficiency gains in agriculture by improving resource allocation. Huang and Rozelle noted that technical change was one of the most important factors that contributed to agricultural growth during the entire reform period, particularly after 1984.

By employing a varying coefficient model, Kalirajan, Obwona, and Zhao found that during the pre-reform period (1970-78) 20 out of 28 provinces had a negative TFP growth in agriculture. However, during the reform period (1978-84) almost all provinces had a positive TFP growth with technical efficiency as the most dominant component, while 16 provinces had a negative TFP growth in the period 1984-1987. Wang, Wailes, and Cramer examined household-level production efficiency by using farm survey data for 1990 and a shadow price profit frontier model and concluded that better educated households and larger farms tend to be more technically efficient. Their results also showed that considerable production inefficiency prevailed both in the emerging inland/deep interior and coastal regions. They recommended that reducing market distortions would increase efficiency.

The purpose of this paper is to investigate the temporal and spacial nature of TFP growth and its components in Chinese agriculture since reforms using nonparametric Malmquist index procedures with provincial-level data (1980-95). The Malmquist approach measures productivity change from one year to the next using the geometric mean of two Malmquist productivity indexes which are constructed using distance functions. Linear programming techniques are used to derive the values of distance functions. Malmquist index approach facilitates a simultaneous examination of productivity growth and its components: technical change and efficiency change. Also, it provides an index measure of productivity change for each province, which helps to assess interprovince disparity in productivity growth and its components and to identify the agricultural productivity trend for the country as a whole.

Our analysis differs from contemporary studies on Chinese agricultural productivity growth with the following features. First, most of the previous studies focused on TFP growth from the institutional reforms, while decomposition of productivity growth into efficiency change and technical change received scant attention, which is a major focus of this paper. Second, the few previous productivity decompositions implicitly assumed that observed production is efficient, which is refutable given that most farms in developing countries operate below full efficiency. The Malmquist index approach does not require the maintained hypothesis of technical and allocative efficiency. Consequently, this approach, rather than assuming full efficiency, estimates production efficiency based on the observed data. Third, previous studies employed a specific functional form, usually the Cobb-Douglas production function, for incorporating technology. In contrast, the Malmquist index approach does not require a specific functional form. Fourth, the approach requires neither data on prices which are not readily available in developing countries nor cost and revenue shares to aggregate inputs and outputs for measuring TFP growth. Finally, most of the previous studies covered only the limited period during the implementation of economic reforms. Our study employs production data from all provinces covering a longer post-reform era (1980-95), which helps to shed light on the disparity in productivity growth among provinces and over time.

Malmquist Productivity Index Procedures

The Malmquist index was first developed by Caves, Christensen, and Diewert and popularized recently by Färe and Grosskopf and others. The Malmquist index has been used to compute productivity growth and its components using aggregate or national-level data and disaggregate or firm-level data. For example, output-based Malmquist productivity indexes were calculated by Färe et al. (1993) for Swedish hospitals, by Färe et al. (1994) for the industrial economies of 17 OECD countries, by Tauer for New York dairy farms, and Färe and Grosskopf (1996a) for the New Zealand economy. Input-based Malmquist indexes were calculated, by Färe et al. (1990) for Illinois electric utilities, by Berg, Forsund, and Jansen for the Norwegian banking industry, by Forsund for Norwegian ferries, and by Thirtle, Piesse, and Turk for the Yugoslav Republics dairy enterprises. Input biased technical change for the Chinese industrial sector was investigated by Färe and Grosskopf (1996b). These applications demonstrate that the Malmquist approach is very useful in studying productivity change in a variety of industries and economies because of its minimal data requirements and considerable computational flexibility.

In this study we used the output-based Malmquist index to measure productivity change in the transitional Chinese agricultural sector. To understand the theoretical framework for the output-based Malmquist productivity index, consider a sample of K observations (or provinces) where each produces S outputs using N inputs at time t. Caves, Christensen, and Diewert showed how to construct a Malmquist productivity index using the ratio of output distance functions for periods t and t+1. The output distance function at time t as defined by Shephard (1970) is:

(1)
$$\begin{aligned} D^t(x^t, y^t) &= inf\{\theta: (x^t, y^t/\theta) \in I^t, \theta \geq 0\}, t, ..., T \\ &= [sup\ \{\theta: (x^t, \theta y^t) \in I^t, \theta \geq 0\}]^{-1} \end{aligned}$$

where θ is a scalar variable and $x^t \in \Re_+^N$ and $y^t \in \Re_+^S$ are the input vector and output vector at time t. The term I^t represents production technology at time t which defines the transformation of inputs into outputs, i.e., $I^t = \{(x^t, y^t): x^t\ can\ produce\ y^t\}$, t=1, ..., T. We assume that I^t satisfies certain axiomatic properties defined by Shephard (1970). The distance function $D^t(x^t, y^t)$ is the reciprocal of Farrell' s measure of technical efficiency, which measures the maximal feasible radial expansion of the output vector y such that the expanded outputs are still producible with a given input vector x.

Table 1 lists the programming models which were used to compute the values of various distance functions used in this study. The value of $D^t(x^t, y^t)$ for observed production and technology in year t can be derived from the solution of the linear programming problem that is specified in model I. The first constraint in model I states that to produce the observed output in the k*th* province at period t, the actual use of input i for province k should be greater than or equal to the theoretically efficient input usage that is a weighted sum of input i for all provinces. The second equation entails that given the actual amount of inputs used by the k*th* province, the maximum feasible output of province k should be less than or equal to the theoretically efficient output that is a weighted sum of all provinces' outputs. Model I imposed constant returns to scale (CRTS) by allowing the elements in the intensity vector z to take any nonnegative values. CRTS technology was also imposed on models I - IV, VII and VIII described in table 1.

The value of $D^{t+1}(x^{t+1}, y^{t+1})$ for observed production in year t+1 with reference to year t+1 technology was computed by applying model I for period t+1 to obtain model II. The mixed period distance function, $D^t(x^{t+1}, y^{t+1})$, involves observations from t+1 with respect to technology at time t and is represented by model III. The first constraint in model III states that to produce the observed level of output y in the k*th* province at time t+1, the actual level of input used by the k*th* province at time t+1should be greater than or equal to the theoretically efficient input use at time t. The second equation indicates that given the actual amount of inputs used by the k*th* province at time t, the maximum feasible output in time t+1 should be less than or equal to the theoretically efficient output produced by all provinces at time t. The value of the mixed period distance function for production in year t with respect to technology at time t+1, $D^{t+1}(x^t, y^t)$, was estimated using model IV which is model III with superscripts t and t+1 interchanged.

Using input-output observations from two periods and ratios of distance functions with reference to technology in each period, Färe and Grosskopf defined a measure of productivity change between these two periods. They denoted the Malmquist productivity change index by $M(x^{t+1}, y^{t+1}, x^t, y^t)$ or $M(\bullet)$ for short defined as the geometric mean of two productivity indexes with respect to technology in periods t and t+1, respectively:

$$(2) \qquad M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[M^t_{CCD} * M^{t+1}_{CCD}\right]^{\frac{1}{2}} = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}}$$

where M^t_{CCD} and M^{t+1}_{CCD} are productivity indexes with reference to technology at time t and t+1 defined by Caves, Christensen, and Diewert.

The Malmquist productivity change index can be decomposed by rewriting (**2**):

$$(3) \qquad M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}\right] = TC * EC$$

where technical change (TC) is measured within the first bracket by the geometric mean of two ratios of distance functions which represent the shift in frontier between years t and t+1 at observed production in year t and t+1, respectively. Efficiency change (EC) is measured within the second bracket by a ratio of two distance functions and records the change in proximity of actual production in each year to maximum feasible production as depicted by the frontier in each year. Unit values for the TC ratio and the EC ratio indicate no change in productivity from t to t+1 from either source. Values greater than (less than) one for the TC term imply technical progress (regression) occurs from t to t+1. Values greater than (less than) one for the EC term imply an improvement in efficiency, movement toward the frontier (deterioration in efficiency, movement away from the frontier). Similarly, unit value of the Malmquist index signals no overall productivity change and values greater than (less than) one for the index indicate productivity growth (regression).

Figure 1 illustrates the Malmquist productivity change index and its components using output distance functions.[1] For illustration purposes, we assume one input is used to produce one output and there are four provinces. In this figure, observations on the actual input-output combinations for four provinces are represented by a (a'), b (b'), c (c'), and d (d') in year t (t+1). The corresponding maximum feasible production for the second province in year t (t+1) is A (D). The CRTS technology is represented by the maximum production frontier OI^{t}_{CRTS} (OI^{t+1}_{CRTS}). Production at time t is technically inefficient for the second province because the observed production (y^t) is less than the maximum feasible production (A). A similar conclusion holds for the first and fourth provinces. Production by the third province is technically efficient in year t because the observed and maximum feasible outputs are equal at B.

The productivity change of the second province is calculated as distances on the output axis. The ratio Oy^t/OA measures the value of $D^t(x^t, y^t)$. In year t+1, the production frontier has advanced to I^{t+1}_{CRTS}, and production of the second province is at b'. The value of $D^{t+1}(x^{t+1}, y^{t+1})$ is measured by the ratio Oy^{t+1}/OD. The value of $D^{t+1}(x^t, y^t)$, evaluating the input-output vector in period t relative to the technology in year t+1, is Oy^t/OC, while the value of $D^t(x^{t+1}, y^{t+1})$, evaluating the input-output vector in period t+1 relative to the technology in year t, is Oy^{t+1}/OB. In figure 1, the Malmquist productivity change index is measured by

(4) $$M(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{Oy^{t+1}/OB}{Oy^{t}/OA}\frac{Oy^{t+1}/OD}{Oy^{t}/OC}\right]^{\frac{1}{2}}$$

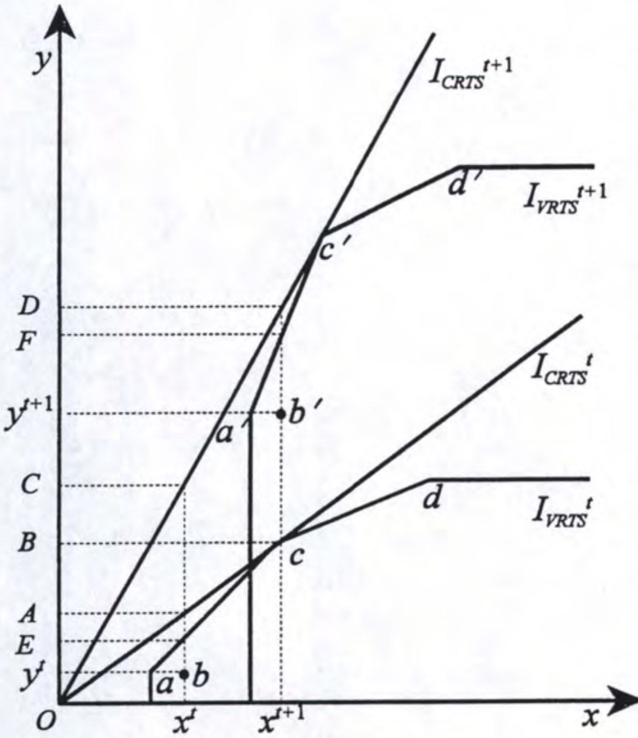

Figure 1. Malmquist Productivity Index and Its Component Measures

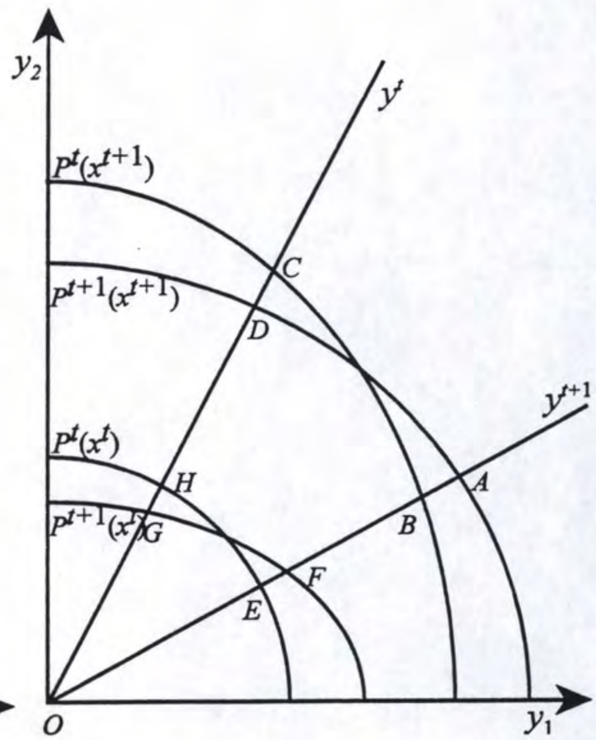

Figure 2. Technical Change and Its Component Measures

The first ratio measures the change in productivity observed between two periods with reference to year t frontier. The second ratio measures the observed change in productivity with reference to year t+1 frontier.

The components of $M(\bullet)$ expressed with the distance functions illustrated in Figure 1are:

$$(5)\quad M\left(x^{t+1},y^{t+1},x^{t},y^{t}\right)=TC*EC=\left[\frac{Oy^{t+1}/OB}{Oy^{t+1}/OD}\;\frac{Oy^{t}/OA}{Oy^{t}/OC}\right]^{\frac{1}{2}}\left[\frac{Oy^{t+1}/OD}{Oy^{t}/OA}\right]=\left[\frac{OD}{OB}\frac{OC}{OA}\right]^{\frac{1}{2}}\left[\frac{OA}{OD}\;\frac{Oy^{t+1}}{Oy^{t}}\right]$$

From (**5**) we see that the innovation effect is measured by the geometric mean of two ratios: OC/OA captures the frontier shift between t and t+1 evaluated at the input vector observed in period t and OD/OB measures the shift in frontier between t and t+1 at the input vector observed in period t+1. The catching-up effect is measured by the change in efficiency or relative efficiency between two periods. Efficiency change is the ratio of the distance between the observation and the frontier in each period.

The efficiency change component in (3) can be decomposed further into scale efficiency change (*SC*) and pure efficiency change (*PC*):

(6)
$$EC = \left[\frac{\dfrac{D^t(x^t, y^t|_{VRTS})}{D^t(x^t, y^t|_{CRTS})}}{\dfrac{D^{t+1}(x^{t+1}, y^{t+1}|_{VRTS})}{D^{t+1}(x^{t+1}, y^{t+1}|_{CRTS})}}\right]\left[\frac{D^{t+1}(x^{t+1}, y^{t+1}|_{VRTS})}{D^t(x^t, y^t|_{VRTS})}\right] = SC*PC$$

The *SC* term measures the change in the ratio of the CRTS frontier to the variable returns to scale (VRTS) frontier between the two periods. The *PC* term measures the change in efficiency with respect to the VRTS frontier. The values of $D^t(x^t, y^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ under VRTS, given respectively by model V and VI, were computed by modifying models I and II to restrict the sum of the elements in the intensity vector z to equal one (Table 1).

In figure 1, the VRTS technology in year t (t+1) is represented by I^t_{VRTS} (I^{t+1}_{VRTS}) which is bounded by $x^t acd$ ($x^{t+1}a'c'd'$). Under the VRTS technology, all but the second province are efficient because the actual and maximum outputs are equal. The values of distance functions for the second province evaluating at b (b') relative to the VRTS technology in year t (t+1) are Oy^t/OE (Oy^{t+1}/OF). The values of distance functions for the same province relative to CRTS technology in year t (t+1) are Oy^t/OA (Oy^{t+1}/OD). Hence, decomposition of the efficiency change component in terms of distances on the output axis is:

(7)
$$EC = \left[\frac{Oy^{t+1}/OD}{Oy^t/OA}\right] = \left[\frac{Oy^t/OE}{Oy^t/OA}\;\frac{Oy^{t+1}/OD}{Oy^{t+1}/OF}\right]^{\frac{1}{2}}\left[\frac{Oy^{t+1}/OF}{Oy^t/OE}\right] = SC*PC$$

Use of modern inputs such as chemical fertilizers have increased substantially in the last two decades in Chinese agriculture. One way to assess this change is to further decompose the *TC* term multiplicatively into measures of output bias (*OB*), input bias (*IB*), and a magnitude component (*MC*) as suggested by Färe and Grosskopf (1996b, p.95).

$$(8)\ TC = \left[\frac{D^{t}(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})}\frac{D^{t+1}(x^{t+1}, y^{t})}{D^{t}(x^{t+1}, y^{t})}\right]^{\frac{1}{2}}\left[\frac{D^{t+1}(x^{t}, y^{t})}{D^{t}(x^{t}, y^{t})}\frac{D^{t}(x^{t+1}, y^{t})}{D^{t+1}(x^{t+1}, y^{t})}\right]^{\frac{1}{2}}\left[\frac{D^{t}(x^{t}, y^{t})}{D^{t+1}(x^{t}, y^{t})}\right] = OB*IB*MC$$

The *OB* term captures whether the input isoquant shifts proportionately for different output mixes and the *IB* term captures whether the output isoquant shifts proportionately for different input mixes.[2] If *OB* (*IB*) is equal to one, technical change is Hicks output (input) neutral. Under joint neutrality (*OB*=*IB*=1), the magnitude term equals technical change, i.e., all technical change is contained within it. If *OB* (*IB*) is not equal to one, technical change is output (input) biased. Note here we utilize the fact that under the CRTS technology output distance functions are reciprocals of input distance functions, i.e., $D^t(x^t,y^t)= D^t(y^t,x^t)^{-1}$ (Fäer and Grosskopf, 1996).

Models VII and VIII in table 1 were used to compute the value of $D^t(x^{t+1}, y^t)$ and $D^{t+1}(x^{t+1}, y^t)$. In model VII both the reference technology and the observed output are from period *t* but the input is from period *t*+1. The output constraint is same as that in model I. The input constraint in model VII states that the actual level of input used by the k*th* province at time *t* should be greater than or equal to the theoretically efficient input use at time *t*+1. In model VIII, the input constraint, the second equation, is same as in model II except that *t* is replaced by *t*+1. However, the maximum feasible output produced by the k*th* province at time *t* should be less than or equal to the theoretically efficient output produced by all provinces at time *t*+1.

The decomposition and measurement of the *TC* component are illustrated in Figure 2.[3] Consider the case of two outputs (y_1, y_2), produced with the given input level x^t (x^{t+1}) at time *t*

(t+1) where the actual outputs are observed at a point on the ray Oy^t (Oy^{t+1}) at time t (t+1). This figure shows four output sets labeled by $P^t(x^t)$, $P^{t+1}(x^t)$, $P^t(x^{t+1})$, and $P^{t+1}(x^{t+1})$, respectively. The output set such as $P^t(x^t) = \{y^t : (x^t, y^t) \in I^t\}$, $t = 1, \ldots, T$ consists of all output vectors y^t that can be produced by the input vector x^t, given technology in year t. Suppose the isoquants *HE* and *GF* for technology in t and t+1 intersect, holding input constant at x^t. The same occurs for the isoquants *CB* and *DA* holding input constant at x^{t+1}. The intersecting isoquants represent extreme cases of output bias. Decomposition of the *TC* term from **(8)** can be depicted as:

$$\textbf{(9)} \qquad TC = OB*IB*MC = \left[\frac{OA}{OB}\frac{OC}{OD}\right]^{\frac{1}{2}} \left[\frac{OH}{OG}\frac{OD}{OC}\right]^{\frac{1}{2}} \left[\frac{OG}{OH}\right] = \left[\frac{OA}{OB}\frac{OG}{OH}\right]^{\frac{1}{2}}$$

The output bias, the first bracketed term, is the square root of the product of two ratios: the ratio *OA/OB* measures the shift in technology between period t and t+1 at the input-output vector observed in period t+1 and the ratio of *OC/OD* captures the shift in frontier at the input level x^{t+1} and the output level y^t. The input bias, the second bracketed term, is the geometric of two ratios: the first ratio measures the technology shift between period t and t+1 evaluated at the input-output vector observed in period t and the second ratio captures the shift in technology at the input level x^{t+1} and the output level y^t. The ratio in the third bracket is the *MC*.

Data

Currently, China has 31 provincial-level units consisting of 23 provinces, four autonomous regions, and four municipalities.[4] Data for the Hainan province were available only after 1988. Prior years' data for Hainan were included in Guangdong.[5] The municipality of Chongqing was established in 1997. Since the study covered the period 1980-95, Chongqing was not included in this study. Consequently, this study included 29 provincial-level units before

1988 and 30 provincial-level units from 1988-95. The provincial-level agricultural input-output data used in this study were from Colby, Crook, and Webb, and *China Rural Statistical Yearbook* for the period 1993 to 1996, and *China Statistical Yearbook* for the same period.

The aggregate output used in this study (in constant 1980 prices) was gross value of agricultural output, excluding village and below-village industry. Six inputs, all measured in physical units, were farm machinery power, irrigation, manure fertilizer, area sown for all crops, chemical fertilizer, and labor force. Farm machinery power (plows, cultivators, irrigators, tractors, etc.) was reported in kilowatts. The irrigation input measured irrigated area with a complete set of irrigation equipment to move adequate water to the fields under normal conditions. Manure fertilizer was computed using the number of agricultural farm animals and rural population by following Fan' s procedure (refer to footnote 8 in Fan). Land input represented area sown under all crops. Since land is frequently sown two or more times a year, sown area is substantially larger than cultivated area. Chemical fertilizer data was reported as total chemical fertilizer application on an effective weight basis. For labor input, we used the number of workers in the agricultural sector.[6]

The following paragraph summarizes agricultural input use and output during 1980-95.[7] Agricultural output grew at an average rate of 6.93% per year for the nation as a whole. Among provinces, Hainan experienced the highest and Qinhai the lowest growth in output, averaging over 10% and 4.24% per year. Shandong was ranked first and Xizang last in terms of gross value of agricultural output. On average, total agricultural output in Shandong and Xizang was valued at 33,164 and 764 million yuan, respectively. These provinces accounted for 10% and about 1% of the country' s value of agricultural output. Chemical fertilizer use grew the fastest, followed by farm machinery use. The growth rate of chemical fertilizer use averaged 8.38% annually with an increase of 12.4% in Qinghai and only 1.9% in Shanghai. The inputs that increased the least were cropland, followed by irrigated area. The growth rate of area sown under all crops averaged only 0.14% annually with an increase of 2.65% in Yunnan and a decrease of 2.34% in Shanghai. About half of the provinces in the coastal region experienced a decrease in agricultural land.

Results and Discussions

In this section, we compute the Malmquist productivity change index and its components and discuss their implications for Chinese agriculture. Linear programs were formulated and run for each model I through VIII in table 1 using GAMS. There was a total of 3,656 linear programming problems covering 30 provinces and 16 years. The various Malmquist index measures were computed from optimal solutions for each of the 30 provinces and for every consecutive pair of years. Before turning to disaggregated results for individual provinces, we present a summary description of the average performance for the nation as a whole.

The TFP growth for the country as a whole increased moderately over time (Table 2). Average change in the Malmquist index over the period 1980 to 1995 was 2.37% annually for the entire nation. This change in productivity was essentially due to progress in shift of the frontier rather than moving-closer to the frontier. On average, technical change contributed to productivity growth by 3.76% per year, while efficiency change reduced productivity by 1.34% per year.[8] Progress in the best-practice technology arose essentially from input-biased technical change which averaged about 2.22% annually. Efficiency deterioration resulted from a decline in pure efficiency and improper scale operation, which decreased productivity respectively by 0.78% and 0.56% per year.

Table 2 also illustrates the temporal pattern of changes in productivity and its components in Chinese agriculture. The Malmquist productivity change index varied from a 8.53% increase in 1983/84 to a 2.95% decrease in 1988/89. Variations in productivity growth due to innovation ranged from an increase of 9.85% in 1983/84 to a decrease of 2.80% in 1988/89, while variations in the catching up effect ranged from an increase of 3.24% in 1980/81 to a decrease of 7.79% in 1994/95. The pattern of Malmquist productivity change over time reveals three subperiods: rapid growth during 1980-84, near stagnation during 1984-89, and rapid growth after 1989. This result corroborates previous findings such as Kalirajan, Obwona, and Zhao. The Kruskal-Wallis nonparametric test results showed that for the three subperiods differences in estimated means of the Malmquist index were statistically significant at the 90% confidence level.[9]

Reforms initiated in 1978 provided strong economic incentives to farmers to use modern technology and inputs and to improve production efficiency. Consequently, during 1980/81-1983/84, both technological innovation and efficiency improvement resulted in higher productivity growth. The frontier shifts augmented the TFP growth by 3.62%, while the catching up effects contributed to productivity growth by 0.10%, resulting in a TFP increase of 3.73%. During 1984/85-1988/89, however, productivity declined by 0.10% per year. TFP regression was mainly due to efficiency deterioration which decreased 1.15% annually, while technical change showed a slight increase. The success in rural reforms during the late 70s and the early 80s encouraged the government to extend economic reforms to urban sectors in 1985. The rapid development of township and village enterprises led to a flow of labor, particularly young and educated farmers, from the agricultural sector to the industrial sector. The introduction of the contract purchase system in 1985 caused a sharp drop in state procurement prices relative to input prices, which resulted in lower farm profitability. These factors led to a productivity decline in the second half of the 1980s (also see Lin, 1992; Kalirajan, Obwona, and Zhao).

This productivity decline caught the attention of policymakers who were concerned with the pace of agricultural output growth, which led to the introduction of further agricultural reforms. Some of these reforms include: raising grain prices by an average of 18% in 1989 (Sicular), ensuring the availability of chemical fertilizers and fuel to contract farmers, and instituting the free-market economy. These reform measures rejuvenated the growth in agricultural productivity. During 1989/90 to 1994/95, productivity grew at an average rate of 3.56% per year. This higher growth contrasts with that in the first half of the 1980s in that the contribution of technical change to productivity growth was even larger.

The decomposition of productivity growth into technical change and efficiency change reveals that the TFP growth in this economic transition period came mainly from progress in the best-practice technology. Some of the key factors behind technical progress as recognized by Stone include the development of chemical fertilizer use, water control technology, cultivation practices (e.g., green houses, plastic sheeting), and new crop varieties (e.g., hybrid, pest and disease resistant varieties in rice and wheat). The catching up effect augmented productivity growth at the beginning of the 1980s and then stagnated. Some of the forces behind efficiency change are institutional reforms (e.g., phasing out central planning, switching from commune farming system to market-oriented production), change in agricultural policies (e.g., reduced tax on farmers, less government intervention), and improvement of managerial skill. Stagnating efficiency change might indicate that the benefit of previous institutional reforms has played out.

Next, we turn our attention to the spatial nature of TFP change at the provincial level. The results reported in Table 3 illustrate the large variability in productivity growth and its components among provinces during this post-reform period. Guangdong province enjoyed the highest TFP growth at 7.64% per year on average, which was due to both the frontier shift effect (6.14%) and the catching up effect (1.41%). This province had the highest rate of efficiency change in the sample, which indicates that Guangdong is more progressive in moving toward the best-practice frontier. At the other extreme, Xizang experienced productivity decline of 3.95% per year, mainly due to technological regression.

Provinces were grouped according to the estimated Malmquist productivity change index into fast-, moderate- and slow-growing groups (Table 3, Figure 3). The differences in estimated means of the TFP change between the three provincial groups were statistically significant using the Kruskal-Wallis test (see endnote 8). The fast productivity growth group includes five provinces, all in the coastal region. Provinces in this group accounted for 13.04% of gross value of agricultural output, 10.78% of grain production, and 8.89% of the arable land in the nation (Table 4). In this group, productivity growth averaged 6.32% per year with the highest growth of 7.64% in Guangdong and the lowest growth of 4.99% in Liaoning. Technical change contributed to productivity growth by 6.36%, while efficiency deterioration reduced productivity growth by 0.03% per year on average.

The moderate productivity growth group consists of 16 provinces, all in the coastal and emerging inland regions. Provinces in this group accounted for 69.63% of gross value of agricultural output, 71.61% of grain production, and 68.37% of the arable land in the nation. On average, productivity grew 2.76% annually with the highest growth of 4.84% in Hainan and the lowest growth of 1.32% in Guangxi. Technical change augmented productivity of this group by 3.96%, while efficiency deterioration eroded productivity by 1.15%.

The slow productivity growth group contains nine provinces, most of them in the underdeveloped deep-interior region. This group produced 17.34% of gross value of agricultural output and 17.61% of grain production with 22.74% of the arable land of the nation. On average, productivity regressed 0.55% annually with a 0.67% increase in Henan and a 3.95% decrease in

Xizang. In this group of provinces, technical change contributed to productivity growth by 1.88%, while poor efficiency performance reduced productivity growth by 2.39%.

It is clear that in all three groups, the lack of efficiency improvement eroded gains from technical change. Therefore, in addition to promoting technical change, efficiency improvement should be a major focus for policymakers, particularly for those provinces in the slow-growing group. To improve the efficiency performance, future reforms should encourage production specialization on the basis of provincial/regional comparative advantage, reduce government intervention in agriculture, and eliminate undue restrictions on output and input movements across the provinces. To augment technical progress, given the limited opportunities to expand the cultivable land, the greatest potential lies in increasing/attracting investment in agricultural research and technological development in agriculture.

The wide disparity in productivity growth among provinces persisted over the entire study period. Some provinces in the coastal region enjoyed faster TFP growth. Some provinces in the emerging inland region exhibited moderate productivity growth. Provinces in the deep interior region experienced a slower growth in productivity. This suggests that differences in productivity growth are related to local conditions such as competitive market pressures, investments, and the ability to safeguard against natural disasters.

Economic reforms in China during the past two-decades have moved farmers into a market-oriented economy. Farmers face greater competitive pressures in the coastal region than in the underdeveloped deep-interior region. Farmers in the coastal area have to constantly improve their managerial skills and adopt new technologies to stay in business. In contrast, farmers in the developing region had less exposure to the market-oriented economy, new information, production organizations, and technologies. Since the level of competitive pressures is an important catalyst to improve production efficiency and promote technological progress, future economic reforms should be directed toward strengthening competitive and market-oriented policies.

The five fast-growing provinces had larger capital investment in agriculture, which accounted for 19.46% of national investment in agriculture with less than 9% of the arable land (Table 4). On average, each province in this group invested 94.99 yuan per hectare per year. The sixteen moderate-growing provinces accounted for 58.65% of national investment in agriculture with 68% of the arable land. Each province invested 49.25 yuan per hectare per year, which is 49% lower than in the fast-growing group. The nine slow-growing provinces had 21.89% of national investment in agriculture with nearly 23% of the arable land. Each province invested 57.21 yuan per hectare per year, which is 40% lower than in the fast-growing group. Further, the fast-growing group had the smallest proportion of cultivated area suffering natural disaster damage, averaging 14.8% of planted acreage. The slow-growing group had the largest proportion of cultivated areas suffering natural disaster damage, averaging 19.11% of the planted acreage. Thus, increasing investment in agriculture and minimizing the damage from the natural disaster (e.g., better flood control, irrigating the land during drought, etc.) for those provinces in moderate- and slow-growing groups would be crucial to promote national productivity growth.

In table 5, we report the disaggregated results in terms of the total number of instances of growth, no change, or regression in productivity for each subperiod and each provincial group. For all periods and provinces, 288 cases (65%) out of a total of 442 showed progressive growth and 154 cases (35%) showed regressive growth. For the frontier shift effect, 316 cases (71%) exhibited progress and 126 cases (29%) exhibited regression. For the input bias term, almost all cases (441) experienced input biased technical change, but input bias decreased over time (Table

2). These results indicate that input biased innovation was a dominant force during this reform period. This is because economic reforms have resulted in substantial change in input prices and mix. For instance, the growth rate of chemical fertilizer use increased by 300% from 1978 to 1990 (Ye and Rozelle). Efficiency change was positive in 123 cases (28%), unchanged in 142 cases (32%), and negative in 177 cases (40%), which indicates that poor efficiency performance was still fairly common over the study period. Removing 142 cases with no change, we examined the remaining 300 cases where efficiency change occurred. In 30.8% of those cases, the efficiency change was due solely to scale efficiency change. In the remaining 69.2% of the cases, the efficiency change was due to both pure efficiency change and scale efficiency change.

Many provinces had productivity growth during 1980-84 and after 1989. About 76% of provinces showed TFP growth in 1980/81-1983/84 and 73% after 1988/89. However, the underlying reasons for the growth in the two periods differ in that innovation played a greater role in enhancing productivity in the latter (87%) than in the former period (67%). More than half of the provinces suffered productivity decline during 1984/85-1988/89. Regressive innovation and deteriorating efficiency performance led to productivity decline in this period. Provinces in the fast-growing group had productivity growth in a larger proportion of years (85%), while provinces in the slow-growing group had productivity growth in only 47% of years. Provinces in the moderate-growing group had productivity growth in 68% of the time. Input biased technical change was smaller for fast-growing group (2.49%) and larger for the slow-growing group (3.15%) (Table 3). This is not unexpected because some agricultural inputs increased much faster in the latter group than the former group. For example, chemical fertilizer use grew at 4.71% and 11.56%, respectively, for the fast- and slow-growing provincial groups. Thus, the input mix changed more dramatically in the slow-growing group and the input biased technical change was greater.

Conclusions

Rapid economic growth and productivity increase have occurred since China embarked on economic reforms. Earlier studies attempted to measure and explain productivity growth in Chinese agriculture by either imposing a functional form on technology or using data covering a shorter reform period. In this study, we investigate total factor productivity (TFP) growth in Chinese agriculture over the period 1980 to 1995 using nonparametric Malmquist procedures. This approach measures productivity change without imposing a functional form nor requiring a cost/revenue share for aggregation. Changes in productivity were explained by separating efficiency change or the catching up effect from technical change or the innovation effect.

For all provinces over the period 1980 to 1995, we found productivity growth in 288 cases out of a total of 442 and regression in 154 cases. Decomposition of productivity growth revealed that technical change increased productivity in 316 cases and decreased productivity in 126 cases. Efficiency performance showed increases in 123 cases, no change in 142 cases, and decreases in 177 cases. The rate of Malmquist productivity change averaged 2.37% per year. Technical change contributed to the growth by 3.76%, while the poor efficiency performance reduced productivity growth by 1.44%. These results indicate that technical change was the dominant force augmenting productivity growth during this post-reform period. A high rate of technical progress and deteriorating efficiency performance coexisted in the Chinese agricultural sector. As Kalirajan, Obwona, and Zhao noted, policies designed to encourage technical progress should be accompanied by successful technological diffusions.

Since this study covered provincial-level data over the period 1980-95, it provides valuable insights into the spatial and temporal nature of TFP growth in Chinese agriculture. The results revealed a wide disparity in productivity growth among provinces. The fast-growing group averaged 6.25% per year. Productivity growth in the moderate- and slow-growing groups showed, respectively, an increase of 2.63% and a decrease of 0.55%. Possible reasons for the wide disparity in productivity growth include the differences in the level of competitive pressures, investments, and safeguard against natural disaster. A U-shaped productivity growth plot was found in this post-reform period: fast growth during 1980/81-1983/84, near stagnation during 1984/85-1988/89, and rapid growth after 1989.

The provincial and temporal disparity in productivity growth reveals the need for different policy measures to be undertaken in various provinces. For all provinces, efficiency-enhancing measures such as market-oriented policies, diffusion of practical agricultural technologies, production specialization, liberalization of government intervention, and removal of undue restrictions on input and output movements across provinces should be promoted. To stabilize productivity growth, measures aimed at reducing the damage from natural disasters should be encouraged in all provinces. More capital investments should be directed to the provinces in the moderate-growing groups. The research and development of new technology together with improvement in catching up performance should be stimulated especially for the provinces in the slow-growing group.

The rapid growth of population and income in China are placing further demands on agricultural systems which have limited opportunities for bringing new land into production. Thus, most of the incremental production to meet growing demand in China must come from higher yields through technological innovation and from more efficient use of its limited agricultural resources. Accordingly, competitive pressure and capital investment should be emphasized to enhance productivity growth in Chinese agriculture for the future.

Endnotes

1. For graphical illustration of an input-based Malmquist productivity index that assumes output is exogenous, see Färe et al. (1992).

2. Following the classical meaning of isoquant, we use the term of input (output) isoquant here because the input (output) is constant and the curve illustrates the output (input) set.

3. The authors would like to thank Rolf Färe and Shawna Grosskopf for their helpful comments on Figure 2.

4. The 23 provinces consist of Anhui, Fujian, Gansu, Guangdong, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan, Zhejiang, and Yunnan. Four autonomous regions include Guangxi, Nei Monggol, Xinjiang, and Xizang. Four municipalities are Beijing, Chongqing, Shanghai, and Tianjin. Four autonomous regions and four municipalities are treated as provinces because for an agricultural purpose they are considered same statistical units as the provinces.

5. Downward adjustment on input-output data was made for Guangdong based on the following relation: $V_{87}^{G} - \left\{1 - (V_{88}^{G} + V_{88}^{H} - V_{87}^{G}) / V_{87}^{G}\right\} * V_{88}^{H}$ where V represents the corresponding input and output variables, G denotes Guangdong, and H stands for Hainan.

6. Labor input by province before 1987 was derived using the same procedure in Fan (see footnote 4 in Fan). Labor data for the period 1987-1995 was obtained from Eric Wailes and Cheng Fang. We gratefully acknowledge their assistance in providing us the data.

7. A table, not reported here in the interest of space limitation, consisting of descriptive statistics of the data including gross value of agricultural outputs and inputs (farm machine power, irrigated area, manure fertilizer, area sown, chemical fertilizer and labor force) is available from the authors upon request.

8. As Färe et al. (1992) noted, variations in efficiency change across provinces within the same period or across years within the same province may offset each other. This may result in the lower mean efficiency change.

9. For three subperiods (provincial groups), the Kruskal-Wallis test statistics for Malmquist productivity index series is 5.56 (23.71). The critical value of $\chi^2_{0.05, 2}$ ($\chi^2_{0.10, 2}$) is 5.99 (4.61).

References

Berg, S.A., F.R. Forsund, and E.S. Jansen. "Malmquist Indices of Productivity Growth during the Deregulation of Norwegian Banking 1980-89." *Scandinavian J. Econ.* 94(1992):5211-28.

Caves, D.W., L.R. Christensen, and W.E. Diewert. "The Theory of Index Numbers and the Measurement of Input, Output, and Productivity." *Econometrica.* 50(November 1982):1393-1414.

China Rural Statistical Yearbook. various issues, Beijing: China Statistical Publishing House.

China Statistical Yearbook. various issues, Beijing: China Statistical Publishing House.

Colby, W.H., W.F. Crook, and S.E. Webb. *Agricultural Statistics of the People Republic of China, 1949-1990.* U.S. Department of Agriculture, Economic Research Service, Statistical Bulletin No. 844. Washington, D.C., 1992.

Fan, S. "Effects of Technological Change and Institutional Reform on Production Growth in Chinese Agriculture." *Amer. J. Agr. Econ.* 73(May 1991):266-75.

Fan, S., and P.G. Pardey. *Agricultural Research in China: Its Institutional Development and Impact.* The Hague: International Service for National Agricultural Research Monograph, 1992.

Färe, R., and S. Grosskopf. *Cost and Revenue Constrained Production.* Springer-Verlag New York, Inc., 1994

_____. "Productivity Growth." In B. Silverstone, A. Bollard, and R. Lattimore (eds.), *A Study of Economic Reform: The Case of New Zealand*, North-Halland, New York, 1996a.

_____. *Intertemporal Production Frontiers: With Dynamic DEA.* Kluwer Academic Publishers, Boston, 1996b.

Färe, R., S. Grosskopf, B. Lindgren, and P. Roos. 1991. "Productivity Changes in Swedish Pharmacies 1980-1989: A Non-Parametric Malmquist Approach." *J. Productivity Analysis.* 3:(1992):85-101.

_____. "Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach." In A. Charnes, W.W. Cooper, A.Y. Lewin, and L.M. Seiford (eds.), *Data Envelopment Analysis: Theory, Methodology, and Application.* Kluwer Academic Publishers, Massachusetts, 1993.

Färe, R., S. Grosskopf, S. Yaisawarng, S. Li, and Z. Wang. "Productivity Growth in Illinois Electric Utilities." *Resour. Energy.* 12(1990):383-98.

Färe, R., S. Grosskopf, M. Norris, and Z. Zhang. "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries." *Amer. Econ. Rev.* 84(March 1994):66-83.

Fleisher, B.M., and Y. Liu. "Economics of Scale, Plot Size, Human Capital, and Productivity in Chinese Agriculture." *Quart. Rev. Econ. Finance.* 32(Autumn 1992):112-23.

Forsund, F.R. "Productivity Growth in Norwegian Ferries." In H.O. Fried, C.A.K. Lovell, and S.S. Schmidt (eds.), *The Measurement of Productivity Efficiency.* Oxford University Press, 1993.

Kalirajan, K.P., M.B. Obwona, and S. Zhao. "A Decomposition of Total Factor Productivity Growth: The Case of Chinese Agricultural Growth before and after Reforms." *Amer. J. Agr. Econ.* 78(May 1996):331-38.

Koo, W.W., and M. Duncan. "Can Developing Countries Afford the New Food System? A Case Study of the Chinese Agricultural Sector." *Amer. J. Agri. Econ.* 79(May 1997): 605-12.

Huang, J., and S. Rozelle. "Technological Change: Rediscovering the Engine of Productivity Growth in China's Agricultural Economy." *J. Development Econ.* 49(July 1996):337-69.

Lin, J.Y. "Endowments, Technology, and Factor Markets: A Natural Experiment of Induced Institutional Innovation from China's Rural Reform." *Amer. J. Agr. Econ.* 77(May 1995):231-42.

______. "Rural Reform and Agricultural Growth in China." *Amer. Econ. Rev.* 82(March 1992):34-51.

______. "Household Farm, Cooperative Farm, Efficiency: Evidence from Rural Decollectivization in China." Paper No. 533, Economic Growth Center Work, Yale University, 1987.

McMillan, J., J. Whalley, and L. Zhu. "The Impact of China's Economic Reforms on Agricultural Productivity Growth." *J. Polit Econ.* 97(August 1989):781-807.

Ma, N.J., P.H. Calkins, and S.R. Johnson. "The Household Responsibility System: Technical and Allocative Efficiency versus Equity." In J.W. Longworth (ed.), *China's Rural Development Miracle, with International Comparison.* University of Queensland, Australia, 1989.

Sicular, T. "Ten Years of Reform: Progress and Setbacks in Agricultural Planning and Pricing." In Y.Y. Kueh and R.F. Ash (eds.), *Economic Trend in Chinese Agriculture: The Impact of Post-Mao Reforms.* Oxford: Clarendon Press, 1993.

Stone, B. "Basic Agricultural Technology under Reform." In Y.Y. Kueh and R.F. Ash (eds.), *Economic Trend in Chinese Agriculture: The Impact of Post-Mao Reforms.* Oxford: Clarendon Press, 1993.

Thirtle, C., J. Piesse, and J. Turk. "The Productivity of Private and Social Farms: Multilateral Malmquist Indices for Slovene Dairying Enterprises." *J. Productivity Analysis.* 7(October 1996):447-60.

U. S. Department of Agriculture (USDA). *China: Situation and Outlook Series.* Washington, D.C: Economic Research Service, June 1997.

Wang, J., E.J, Wailes, and G.L. Cramer. "A Shadow-Price Frontier Measurement of Profit Efficiency in Chinese Agriculture." *Amer. J. Agr. Econ.* 78(January 1995):146-56.

Wang, J., G.L. Cramer, and E.J, Wailes. "Production Efficiency of Chines Agriculture: Evidence from Rural Household Survey Data." *Agri. Econ.* 15(September 1996):17-28

Ye, Q., and S. Rozelle. "Fertilizer Demand in China' s Reforming Economy." *Canadian J. Agri. Econ.* 42(July 1994):191-207.

Table 1. Distance Function and the Linear Programming Model

Model I	Model II	Model III	Model IV
$\left[D^{t}\left(x_{ik}^{t}, y_{k}^{t} \mid_{CRTS}\right)\right]^{-1}$	$\left[D^{t+1}\left(x_{ik}^{t+1}, y_{k}^{t+1} \mid_{CRTS}\right)\right]^{-1}$	$\left[D^{t}\left(x_{ik}^{t+1}, y_{k}^{t+1} \mid_{CRTS}\right)\right]^{-1}$	$\left[D^{t+1}\left(x_{ik}^{t}, y_{k}^{t} \mid_{CRTS}\right)\right]^{-1}$
$\underset{(z,\ \theta)}{Max}\ \theta_k$ $s.t.\ \sum_{k=1}^{K} x_{ik}^{t} z_{k}^{t} - x_{ik}^{t} \le 0 \quad \forall\ i$ $\sum_{k=1}^{K} y_{k}^{t} z_{k}^{t} - \theta_k y_{k}^{t} \ge 0$ $z_k \ge 0,\ \theta_k = free$	As in model I, except the superscrip *t* is replaced by *t*+1	$\underset{(z,\ \theta)}{Max}\ \theta_k$ $s.t.\ \sum_{k=1}^{K} x_{ik}^{t} z_{k}^{t} - x_{ik}^{t+1} \le 0 \quad \forall\ i$ $\sum_{k=1}^{K} y_{k}^{t} z_{k}^{t} - \theta_k y_{k}^{t+1} \ge 0$ $z_k \ge 0,\ \theta_k = free$	The superscripts *t* and (*t*+1) in model III are transposed

Model V	Model VI	Model VII	Model VIII
$\left[D^{t}\left(x_{ik}^{t}, y_{k}^{t} \mid_{VRTS}\right)\right]^{-1}$	$\left[D^{t+1}\left(x_{ik}^{t+1}, y_{k}^{t+1} \mid_{VRTS}\right)\right]^{-1}$	$\left[D^{t}\left(x_{ik}^{t+1}, y_{k}^{t} \mid_{CRTS}\right)\right]^{-1}$	$\left[D^{t+1}\left(x_{ik}^{t+1}, y_{k}^{t} \mid_{CRTS}\right)\right]^{-1}$
model I plus $\sum_{k=1}^{K} z_{k}^{t} - 1 = 0$	model II plus $\sum_{k=1}^{K} z_{k}^{t+1} - 1 = 0$	$\underset{(z,\ \theta)}{Max}\ \theta_k$ $s.t.\ \sum_{k=1}^{K} x_{ik}^{t} z_{k}^{t} - x_{ik}^{t+1} \le 0 \quad \forall\ i$ $\sum_{k=1}^{K} y_{k}^{t} z_{k}^{t} - \theta_k y_{k}^{t} \ge 0$ $z_k \ge 0,\ \theta_k = free$	$\underset{(z,\ \theta)}{Max}\ \theta_k$ $s.t. \sum_{k=1}^{K} x_{ik}^{t+1} z_{k}^{t+1} - x_{ik}^{t+1} \le 0 \quad \forall\ i$ $\sum_{k=1}^{K} y_{k}^{t+1} z_{k}^{t+1} - \theta_k y_{k} \ge 0$ $z_k \ge 0,\ \theta_k = free$

Note: θ=a scalar variable measuring the level of efficiency, x_{ik}=the actual quantity of the i*th* input used by the k*th* province, y_k=the output produced by k*th* province (we are considering only one output, i.e., gross value of agricultural output), z=a K-dimensional vector of intensity variable to be estimated, CRTS=constant returns to scale, and VRTS=variable returns to scale.

Table 2. Changes in Agricultural Productivity and Its Components for all Provinces: 1980-1995

Year	M(•)	TC	IB	MC	EC	SC	PC
Subperiod (80/81 -83/84)							
80/81	1.0267	0.9945	1.0292	0.9663	1.0324	1.0123	1.0199
81/82	1.0426	1.0831	1.0317	1.0498	0.9626	0.9713	0.9911
82/83	0.9964	0.9745	1.0342	0.9423	1.0224	1.0239	0.9985
83/84	1.0853	1.0985	1.0206	1.0762	0.9880	0.9969	0.9911
Average	1.0373	1.0362	1.0289	1.0071	1.0010	1.0009	1.0001
Subperiod (84/85-88/89)							
84/85	1.0366	1.0515	1.0274	1.0235	0.9859	0.9833	1.0027
85/86	0.9837	1.0165	1.0248	0.9919	0.9678	0.9815	0.9861
86/87	1.0195	1.0161	1.0171	0.9990	1.0034	0.9817	1.0221
86/88	0.9863	0.9990	1.0348	0.9654	0.9873	1.0260	0.9623
88/89	0.9705	0.9720	1.0194	0.9535	0.9985	0.9791	1.0198
Average	0.9990	1.0107	1.0247	0.9863	0.9885	0.9901	0.9983
Subperiod (89/90-94/95)							
89/90	1.0273	1.0497	1.0162	1.0330	0.9787	0.9905	0.9880
90/91	1.0544	1.0321	1.0175	1.0145	1.0216	1.0521	0.9710
91/92	1.0433	1.0805	1.0177	1.0617	0.9655	0.9709	0.9945
92/93	1.0437	1.0423	1.0107	1.0313	1.0013	1.0011	1.0002
93/94	1.0395	1.0747	1.0199	1.0537	0.9672	0.9746	0.9925
94/95	1.0064	1.0914	1.0126	1.0778	0.9221	0.9424	0.9784
Average	1.0356	1.0616	1.0158	1.0451	0.9756	0.9880	0.9874
Minimum	0.9705	0.9720	1.0107	0.9423	0.9221	0.9424	0.9623
Maximum	1.0853	1.0985	1.0348	1.0778	1.0324	1.0521	1.0221
Mean	1.0237	1.0376	1.0222	1.0151	0.9866	0.9922	0.9944
Std. Dev.	0.0307	0.0421	0.0077	0.0447	0.0283	0.0273	0.0172

Note: M(•) = Malmquist productivity change index, TC = technical change, IB = input bias, MC = magnitude component, EC = efficiency change, SC = scale change, and PC = pure efficiency change.

The values in this table minus one multiplied by 100 give percent changes in productivity growth and its components.

In this study, the output bias is equal to one (therefore omitted for reporting) because there was only one output (see Färe and Grosskopf, 1996b).

Table 3. Changes in Agricultural Productivity and Its Components for 30 Provinces

Province	M(•)	Std Dev	TC	IB	MC	EC	SC	PC
Fast-Growing Provincial Group								
Guangdong	1.0764	0.0645	1.0614	1.0063	1.0547	1.0141	1.0024	1.0117
Beijing	1.0714	0.0601	1.0714	1.0357	1.0345	1.0000	1.0000	1.0000
Shanghai	1.0645	0.0869	1.0645	1.0675	0.9972	1.0000	1.0000	1.0000
Fujian	1.0540	0.0531	1.0604	1.0068	1.0533	0.9939	0.9939	1.0000
Liaoning	1.0499	0.0773	1.0601	1.0098	1.0498	0.9904	0.9904	1.0000
Mean	1.0632	0.0684	1.0636	1.0249	1.0377	0.9997	0.9973	1.0023
Moderate-Growing Provincial Group								
Hainan	1.0484	0.1119	1.0484	1.0721	0.9778	1.0000	1.0000	1.0000
Tianjin	1.0466	0.0885	1.0394	1.0304	1.0087	1.0069	1.0069	1.0000
Jiangsu	1.0401	0.0488	1.0515	1.0112	1.0399	0.9891	0.9891	1.0000
Zhejiang	1.0391	0.0562	1.0391	1.0225	1.0163	1.0000	1.0000	1.0000
Jilin	1.0335	0.1110	1.0470	1.0056	1.0413	0.9871	0.9872	0.9999
Shandong	1.0334	0.0944	1.0492	1.0046	1.0445	0.9849	0.9849	1.0000
Jiangxi	1.0313	0.0588	1.0391	1.0049	1.0341	0.9925	0.9925	1.0000
Shaanxi	1.0303	0.0571	1.0396	1.0021	1.0374	0.9910	0.9926	0.9984
Hubei	1.0265	0.0640	1.0429	1.0014	1.0415	0.9843	0.9900	0.9942
Xinjiang	1.0200	0.0710	1.0302	1.0181	1.0119	0.9901	0.9943	0.9958
Heilongjiang	1.0178	0.0957	1.0178	1.0592	0.9609	1.0000	1.0000	1.0000
Hebei	1.0172	0.0431	1.0414	1.0013	1.0398	0.9767	0.9788	0.9979
Sichuan	1.0166	0.0645	1.0206	1.0281	0.9927	0.9961	0.9961	1.0000
Hunan	1.0152	0.0394	1.0398	1.0015	1.0382	0.9764	0.9851	0.9911
Anhui	1.0142	0.0782	1.0445	1.0014	1.0433	0.9710	0.9828	0.9880
Guangxi	1.0132	0.0619	1.0442	1.0030	1.0410	0.9703	0.9858	0.9843
Mean	1.0276	0.0715	1.0396	1.0165	1.0228	0.9885	0.9916	0.9968
Slow-Growing Provincial Group								
Henan	1.0067	0.0824	1.0492	1.0019	1.0472	0.9595	0.9767	0.9825
Qinghai	1.0063	0.0819	1.0257	0.9996	1.0262	0.9811	0.9811	1.0000
Guizhou	1.0061	0.0751	1.0182	1.0208	0.9975	0.9881	0.9977	0.9904
Ningxia	1.0026	0.0750	1.0343	1.0051	1.0291	0.9693	1.0091	0.9606
Gansu	1.0002	0.0629	1.0197	1.0015	1.0182	0.9809	0.9940	0.9867
Shanxi	0.9999	0.0801	1.0399	1.0004	1.0395	0.9616	0.9858	0.9754
Yunnan	0.9953	0.0552	1.0319	1.0065	1.0253	0.9645	0.9815	0.9827
Nei Monggol	0.9738	0.0752	0.9928	1.0270	0.9667	0.9809	0.9870	0.9938
Xizang	0.9605	0.2290	0.9605	1.2422	0.7732	1.0000	1.0000	1.0000
Mean	0.9945	0.0908	1.0188	1.0315	0.9877	0.9761	0.9903	0.9857

Note: see the notes in Table 2 for variable definition.

Table 4. Data on the Selected Variables for the Provincial Groups

Provincial Group	Number of Province	Gross Value of Agricultural Output (%)	Total Grain Production (%)	Area Sown under all Crops (%)	Total Agricultural Capital Investments[a]		Severe Damage from Natural Disasters[b]	
					Percent (%)	Average (yuan/ha.)	Percent (%)	Percent[c] (%)
Fast-growing	5	13.04	10.78	8.89	19.46	94.99	8.82	14.80
Moderate-growing	16	69.63	71.61	68.37	58.65	49.25	65.80	15.32
Slow-growing	9	17.34	17.61	22.74	21.89	57.21	25.38	19.00
Total	30	100.00	100.00	100.00	100.00	-	100.00	-
Average	-	-	-	-	-	65.15	-	16.37

[a]Data for agricultural capital construction investment covers the period 1981-92. Average investment per hectare was calculated by dividing agricultural capital investment by area sown under all crops over the period 1981-1992.

[b]Data for cultivated area suffering severe damage from natural disaster covers the period 1983-95. Natural disaster includes flood, drought, frost, freeze, wind, and hail damage.

[c]This percentage was calculated by dividing cultivated area suffering severe damage from natural disaster by area sown under all crops for the period of 1983-95.

Table 5. Changes in the Malmquist Productivity Index and Its Components: 1980-1995 and 30 Provinces

		M(•)		TC		IB		MC		EC			SC			PC		
		>1	<1	>1	<1	≠1	=1	>1	<1	>1	=1	<1	>1	=1	<1	>1	=1	<1
<u>Subperiod</u>																		
80/81-83/84	Total	88	28	78	38	116	0	72	44	39	40	37	36	40	40	31	58	27
	%	76	24	67	33	100	0	62	38	34	34	32	31	34	34	27	50	23
84/85-88/89	Total	69	77	82	64	146	0	69	77	41	50	55	35	50	61	31	78	37
	%	47	53	56	44	100	0	47	53	28	34	38	24	34	42	21	53	25
89/90-94/95	Total	131	49	156	24	179	1	146	34	43	52	85	51	52	77	29	98	53
	%	73	27	87	13	99	1	81	19	24	29	47	28	29	43	16	54	29
Grand total		288	154	316	126	441	1	287	155	123	142	177	122	142	178	91	234	117
%		65	35	71	29	100	0	65	35	28	32	40	28	32	40	21	53	26
<u>Provincial Group</u>																		
Fast-growing	Total	70	12	63	19	82	0	55	27	19	44	19	19	44	19	8	69	5
	%	85	15	77	23	100	0	67	33	23	54	23	23	54	23	10	84	6
Moderate-growing	Total	154	71	166	59	225	0	152	73	63	70	92	62	70	93	51	115	59
	%	68	32	74	26	100	0	68	32	28	31	41	28	31	41	23	51	26
Slow-growing	Total	64	71	87	48	135	1	80	55	41	28	66	41	28	66	32	50	53
	%	47	53	64	36	99	1	59	41	30	21	49	30	21	49	24	37	39
Grand total		288	154	316	126	441	1	287	155	123	142	177	122	142	178	91	234	117
%		65	35	71	29	100	0	65	35	28	32	40	28	32	40	21	53	26

Note: M(•) = Malmquist productivity change index, TC = technical change, IB = input bias, MC = magnitude component, EC = efficiency change, SC = scale change, and PC = pure efficiency change, >1 = growth, <1 = regression, and =1 = no change.

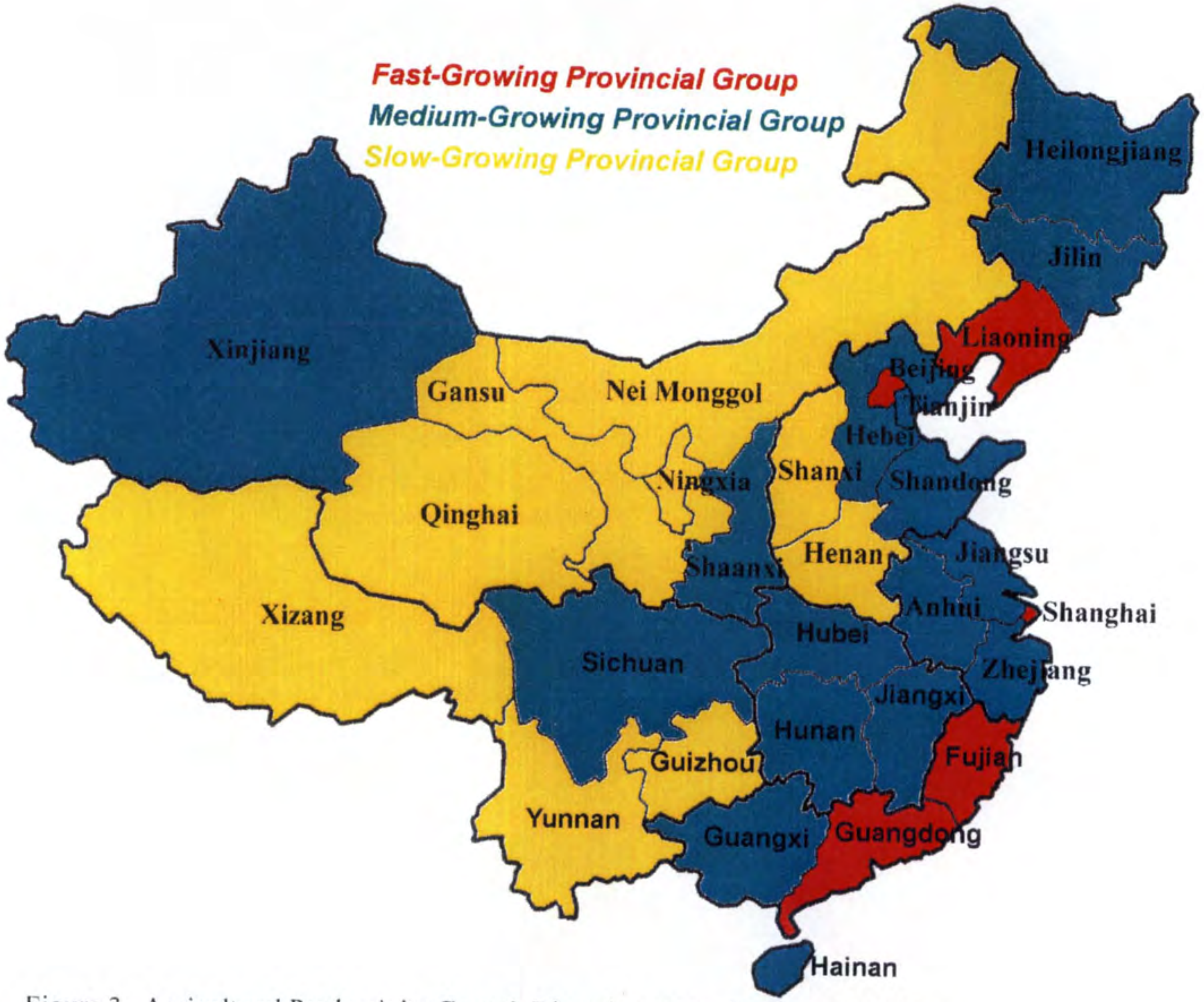

Figure 3. Agricultural Productivity Growth Disparity among Provinces in China