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Parametric Decomposition of the Malmquist Index in an Output-Oriented Distance Function

Productivity in Chinese Agriculture

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ABSTRACT

The paper extends the methodology of parametric decomposition of the Malmquist productivity index using an output distance function. This approach addresses common methodological issues in total factor productivity estimation to produce credible and relevant results. The Malmquist index can be decomposed into several components: technical change (further broken down into technical change magnitude, input bias, and output bias), technical efficiency change, scale efficiency change, and output-mix effect. A translog output distance function is chosen to represent the production technology, and each component of the Malmquist index is computed using the estimated parameters. This parametric approach allows us to statistically test hypotheses regarding different components of the Malmquist index and the nature of production technology. The empirical application to Chinese agriculture shows that productivity grows at 2 percent per year on average from 1978 through 2010. The growth is mostly driven by technical change, which is found to be technology neutral.

Keywords: Malmquist index, output distance function, translog, bias, scale efficiency, Chinese agriculture

JEL classification: C12, C23, D24, Q10

1. INTRODUCTION

Productivity change is defined as the ratio of change in outputs to change in inputs. Caves, Christensen, and Diewert (1982) introduced the Malmquist index to measure productivity through distance functions. Färe et al. (1994) showed that the index can be directly estimated using nonparametric techniques like data envelopment analysis (DEA). They also developed the decomposition of the Malmquist index into two mutually exclusive and exhaustive components: technical change and efficiency change. Many researchers have since extended that decomposition to develop a more detailed analysis of the Malmquist index, including several alternative approaches to understand technical change and scale efficiency (Färe et al. 1997; Balk 2001; Lovell 2003; Ray 2003).

The majority of Malmquist index estimation falls under the nonparametric DEA approach (Färe, Grosskopf, and Roos 1998). The DEA approach estimates the Malmquist index and its components through the calculation of distance functions under both constant and variable returns-to-scale technologies. The popularity of DEA stems from the advantages of the nonparametric approach: easy to compute, applicable in cases of multiple outputs, no assumptions of economic behavior such as cost minimization or profit maximization, no need for price information, neither any particular functional form for estimation nor a large number of observations. Such features are attractive in cases where price data are unavailable or cannot be constructed in detail, the sample is too small, or there is insufficient understanding of firm behavior. However, the nonparametric approach cannot provide a way to directly test the statistical significance or hypotheses regarding the significance of the assembling components or model specification. It also cannot separate measurement errors and random noise from technical inefficiency.

The parametric approach provides a solution to address the shortcomings of nonparametric techniques and has been adopted by some recent studies in the estimation of the Malmquist index (Balk 2001; Fuentes, Grifell-Tatje, and Perelman 2001; Pantzios, Karagianis, and Tzouvelekas 2011). In the parametric approach, the Malmquist index is not directly obtained through the estimation of distance functions under different returns-to-scale technologies. Instead the Malmquist index and its components are calculated based on the fitted distance function with globally variable returns to scale, evaluated at adjacent time periods' input and output quantities, as implemented by Balk (2001), Fuentes, Grifell-Tatje, and Perelman (2001), Orea (2002), and Pantzios, Karagianis, and Tzouvelekas (2011). In addition to statistical testing, the parametric approach has the advantages of accommodating random errors and enabling different interactions between outputs and inputs if a flexible functional form is chosen to closely approximate the underlying production technology.

This paper extends the methodology of Balk (2001) and Färe et al. (1997) to decompose the Malmquist index into different components while simultaneously taking account of technology bias and scale efficiency change. We test some hypotheses regarding the production technology, functional specification, and returns to scale by imposing parametric restrictions in the estimation. The hypotheses include (1) no technical inefficiency; (2) no heterogeneous inefficiency effect; (3) no technical change; (4) production technology exhibits input Hicks neutrality (no input bias); (5) output Hicks neutrality (no output bias); (6) input and output Hicks neutrality; (7) input-output separability; (8) Cobb-Douglas functional form; and (9) constant returns to scale (CRS). The test of each hypothesis examines the corresponding components of the Malmquist index. If the technical efficiency term is statistically not different from zero, there will be no efficiency change and the contribution of efficiency change to productivity growth will be zero. If technical change or its components are insignificant, no productivity growth comes from improvement in the production frontier. If the functional form can be simplified to the Cobb-Douglas function, the production technology becomes time invariant and separable. Finally, if the hypothesis of constant returns to scale is not rejected, the scale effect term disappears from the Malmquist index.

By answering these questions, the paper adds value to the existing literature in several ways. First, it decomposes the Malmquist productivity index into different components using an output distance function. Unlike Pantzios, Karagianis, and Tzouvelekas (2011), the decomposition of this paper is based on the geometric mean of two adjacent Malmquist indexes, filling a gap in the existing literature of productivity analysis. Second, it demonstrates the advantages of the parametric output distance function approach to characterizing the agricultural technology and productivity decomposition. The empirical model is a four-output, four-input stochastic output distance function in 31 Chinese provinces over the 1979–2010 period. This technique is appropriate for the issue at hand because it requires only quantity data on inputs and outputs, which are well recorded and easily accessible. It does not require price information, which is hard to collect and construct. Third, the parametric approach addresses common methodological issues in total factor productivity (TFP) estimation like testing hypotheses regarding the production technology, which has been lacking in the empirical literature. For example, the hypothesis of input-output separability is rejected, which suggests that results from a stochastic production function can be misleading. This technique can also be applied to other economic investigations of productivity in various settings to produce credible and relevant results. Finally, this paper updates the productivity performance of the whole agricultural sector in China with the latest data, adding evidence for the purpose of designing agricultural development strategy in the developing country context. We found that TFP grows at 2 percent annually in China, which is consistent with other studies of the country. The results have important implications in the design of policy to promote productivity growth in China. For example, past agricultural policies have failed to address China's huge efficiency gap so as to decrease the wasteful use of agricultural inputs and reduce costs to the environment. Whether productivity can be improved through a shift in current technology is another relevant issue worth exploring. Additionally, given the considerable spatial variation, agricultural development policies need to be tailored to local conditions during planning and implementation.

The paper is organized as follows. Section 2 presents the theoretical framework of the decomposition of the Malmquist index based on an output-oriented distance function. Assuming a translog output distance function, the parametric calculation of different components of the Malmquist index is derived in Section 3. The data and empirical results are discussed in Sections 4 and 5. Section 6 concludes with the major findings and policy implications derived from the study.

2. THEORETICAL FRAMEWORK OF MALMQUIST INDEX DECOMPOSITION

The production technology is defined as the set of all feasible input-output combinations. The production technology T in period t is

$$T^t = (x^t, y^t), \mathrm{t} = 1, \dots, \mathrm{T}, \tag{1}$$

where x^t is a *K*-dimensional vector of nonnegative inputs $x^t \equiv (x_1^t, \dots, x_K^t) \in \Re_+^K$, y^t is an *M*-dimensional vector of nonnegative outputs $y^t \equiv (y_1^t, \dots, y_M^t) \in \Re_+^M$, and T^t is the production possibility set for all feasible input-output combinations in period *t*.

The output distance function $\mathrm{D_o^t(x^t, y^t)}$ is measured as the distance of a vector of inputs and outputs in period t with respect to the technical frontier in period t:

$$D_o^t(x^t, y^t) = \min\{\theta > 0 : (x^t, y^t/\theta) \in T\}, \mathrm{t} = 1, \dots, \mathrm{T}, \tag{2}$$

where subscript *o* refers to output orientation. The output distance function satisfies the inequality $D_o^t(x^t, y^t) \leq 1$. $D_o^t(x^t, y^t) = 1$ indicates that the production unit is on the frontier of the production set and hence is technically efficient.

The Malmquist index measures the TFP change between two adjacent periods by calculating the ratio of the distance of each data point relative to a common technological frontier. Following Färe et al. (1994), the Malmquist index between period t and t + 1 based on the period t technology is given by

$$TFP_o^t(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}. \tag{3}$$

The Malmquist index can be greater than, equal to, or less than 1 if productivity grows, is stagnant, or declines between the two periods.

Similarly, the Malmquist index between period t and t + 1 based on the period t + 1 technology is

$$TFP_o^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}. \tag{4}$$

Measures of the productivity change between period t and t + 1 generally change if the reference technology is different. To avoid the arbitrary choice of reference technology, Färe et al. (1994) suggested a geometric mean of the two Malmquist indexes:

$$TFP_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right]^{1/2}. \tag{5}$$

Balk (2001) showed that the Malmquist index can be decomposed into four components: primal technical change (TC), technical efficiency change (EC), scale efficiency change (SEC), and output-mix effect (OME):

$$TFP = TC \cdot EC \cdot SEC \cdot OME, \tag{6}$$

where

$$TC = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right]^{1/2}, \tag{7}$$

$$\mathrm{EC} = \frac{\mathrm{D_o^{t+1}(x^{t+1}, y^{t+1})}}{\mathrm{D_o^t(x^t, y^t)}}, \tag{8}$$

$$SEC = \left[\frac{OSE^t(x^{t+1}, y^t)}{OSE^t(x^t, y^t)} \frac{OSE^{t+1}(x^{t+1}, y^{t+1})}{OSE^{t+1}(x^t, y^{t+1})}\right]^{1/2}, \tag{9}$$

and
$$OME = \left[\frac{OSE^t(x^{t+1}, y^{t+1})}{OSE^t(x^{t+1}, y^t)} \frac{OSE^{t+1}(x^t, y^{t+1})}{OSE^{t+1}(x^t, y^t)}\right]^{1/2}. \tag{10}$$

The magnitude of the first term, TC, in general depends on the particular input-output combination. There is technical progress when TC is greater than 1 and technical regress when it is less than 1. If $\mathrm{TC(x^{t+1}, y^{t+1}) = TC(x^t, y^t)}$, the technical change is output neutral.

The technical efficiency, $\mathrm{TE = D_o^t(x^t, y^t)}$, measures the distance of the firm's position in period t relative to the period t frontier of the technology, or how far the observed production is from maximum potential production. By definition $\mathrm{TE} \leq 1$, and the production unit is efficient if and only if $\mathrm{TE} = 1$. The second term, EC, measures technical efficiency change between period t and t + 1. If EC is greater than 1, the production unit moves closer to the frontier—in other words, the production unit is catching up to the production frontier by improving efficiency. A value of less than 1 indicates efficiency regress.

The third term, SEC, refers to scale efficiency change between two periods, which measures how the output-oriented scale efficiency changes over time conditional on a certain output mix. It is the ratio of the output-orientated measure of scale efficiency (OSE) in period t and t + 1, where $\mathrm{OSE^t(x^t, y^t)} = \frac{\widetilde{\mathrm{D_o^t}}(\mathrm{x^t, y^t})}{\mathrm{D_o^t(x^t, y^t)}}$ and $\widetilde{\mathrm{D_o^t}}(\mathrm{x^t, y^t})$ is the output distance function based on the cone technology $\widetilde{\mathrm{T^t}} = \{(\lambda \mathrm{x^t}, \lambda \mathrm{y^t}) | (\mathrm{x^t, y^t}) \in \mathrm{T^t}, \lambda > 0\}$. If OSE = 1, the frontier point that can be reached by proportionally expanding $\mathrm{y^t}$ is a point of technically optimal scale. At that point, the technology exhibits constant returns to scale and scale elasticity equals 1: $\epsilon_\mathrm{o}^\mathrm{t}(\mathrm{x^t, y^t}) = 1$. If SEC is greater than 1, the output bundle at period t + 1 lies closer to the point of the technically optimal than the output bundle at period t and thus scale efficiency improves. If SEC is less than 1, the scale efficiency deteriorates.

The fourth term is labeled the output-mix effect by Balk (2001), which measures how the distance of the frontier point to the frontier of the cone technology changes when the output mix changes, where the cone technology is the technology generated from the underlying observed technology. That is, OME gives the change in the output-oriented scale efficiency from a change in the output mix when inputs remain constant. When the output mix changes, the scale efficiency increases if OME is greater than 1, and scale efficiency declines if OME is less than 1. In the case of a single output, OME = 1. Under global constant returns to scale technology, both SEC and OME are identically equal to 1.

Färe et al. (1997) suggest that the technical change component can be further decomposed to allow determining the contribution of technical change neutrality in productivity change:

$$\begin{aligned} TC &= \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} = \frac{\mathrm{D_o^t(x^t, y^t)}}{\mathrm{D_o^{t+1}(x^t, y^t)}} \left[\frac{\mathrm{D_o^t(x^{t+1}, y^{t+1})}}{\mathrm{D_o^{t+1}(x^{t+1}, y^{t+1})}} \frac{\mathrm{D_o^{t+1}(x^t, y^t)}}{\mathrm{D_o^t(x^t, y^t)}}\right]^{\frac{1}{2}} \\ &= \frac{\mathrm{D_o^t(x^t, y^t)}}{\mathrm{D_o^{t+1}(x^t, y^t)}} \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^{t+1}(x^{t+1}, y^t)}{D_o^t(x^{t+1}, y^t)}\right]^{\frac{1}{2}} \left[\frac{D_o^t(x^{t+1}, y^t)}{D_o^{t+1}(x^{t+1}, y^t)} \frac{D_o^{t+1}(x^t, y^t)}{D_o^t(x^t, y^t)}\right]^{\frac{1}{2}} \\ &= TCM \cdot OB \cdot IB, \end{aligned} \tag{11}$$

where
$$\mathrm{TCM} = \frac{\mathrm{D_o^t(x^t, y^t)}}{\mathrm{D_o^{t+1}(x^t, y^t)}}, \tag{12}$$

$$\text{OB} = \left[\frac{D_o^t(x^{t+1},y^{t+1})}{D_o^{t+1}(x^{t+1},y^{t+1})}\frac{D_o^{t+1}(x^{t+1},y^t)}{D_o^t(x^{t+1},y^t)}\right]^{1/2}, \tag{13}$$

and

$$\text{IB} = \left[\frac{D_o^t(x^{t+1},y^t)}{D_o^{t+1}(x^{t+1},y^t)}\frac{D_o^{t+1}(x^t,y^t)}{D_o^t(x^t,y^t)}\right]^{1/2}. \tag{14}$$

TCM is the index of technical change magnitude. It is greater than 1 if the input requirement set expands along a ray through period *t* data, and less than 1 if the input requirement set shrinks. OB refers to the period *t + 1* output bias index. It compares the magnitude of technical change along a ray through y^{t+1} with the magnitude of technical change along a ray through y^t while holding the input vector constant at x^{t+1}. The period *t* input bias index (IB) compares the magnitude of technical change along a ray through x^{t+1} with the magnitude of technical change along a ray through x^t, holding the output vector constant at y^t. The bias indexes OB and IB are greater than 1 if the magnitude of technical change measured along a ray through period *t* + 1 data exceeds the magnitude of technical change measured along a ray through period *t* data, and vice versa. Färe et al. (1997) prove that OB (IB) is equal to 1 if the technology is said to exhibit implicit Hicks output-neutral (input-neutral) technical change. In other words, the output (input) set shifts in or out by the same proportion along a ray through period *t* + 1 data as it does along the ray through period *t* data. OB equals 1 in the case of a single output and IB equals 1 in the case of a single input.

3. PARAMETRIC ESTIMATION OF THE MALMQUIST INDEX

Unlike the nonparametric DEA approach, the parametric approach requires a predefined functional form of the distance function for estimation. According to Coelli and Perelman (2000), this specification fulfills a set of desirable characteristics: flexible, easy to derive, and allowing the imposition of homogeneity. The flexible form of the translog has been widely used to estimate distance functions as it meets all the required characteristics (Balk 2001; Orea 2002; Ray 2003; Kounetas and Tsekouras 2007; Pantzios, Karagianis, and Tzouvelekas 2011). This paper will also adopt the translog functional form.

The period *t* technology is represented by the translog output distance function

$$
\begin{aligned}
ln\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{x}^{\mathrm{t}},\mathrm{y}^{\mathrm{t}}) &= \alpha_0 + \sum_{k=1}^{K}\alpha_k lnx_k^t + \sum_{m=1}^{M}\beta_m lny_m^t + \frac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K}\alpha_{kk'} lnx_k^t lnx_{k'}^t \\
&+ \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\beta_{mm'} lny_m^t lny_{m'}^t + \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{km} lnx_k^t lny_m^t + \sum_{k=1}^{K}\delta_{kt} lnx_k^t t \\
&+ \textstyle\sum_{m=1}^{M}\tau_{mt} lny_m^t t + \theta_t t + \frac{1}{2}\theta_{tt}t^2, x \in \Re_+^K, y \in \Re_+^M. \qquad (15)
\end{aligned}
$$

The parameters must satisfy a set of restrictions. First, the condition of linear homogeneity in outputs is imposed to obtain an output-oriented radial distance function:

$\sum_{m=1}^{M}\beta_m = 1,\ \sum_{m'=1}^{M}\beta_{mm'} = 0,\ \sum_{m=1}^{M}\tau_{mt} = 0,\ \sum_{m=1}^{K}\gamma_{km} = 0.$

Second, symmetry is applied:

$\alpha_{kk'} = \alpha_{k'k},\ \beta_{mm'} = \beta_{m'm}.$

The output distance function (15) is expressed as $lnD_o^t = TL(x^t, y^t, t; \pi)$ for notational convenience, where *TL* denotes the translog function specification and $\pi = (\alpha, \beta, \gamma, \delta, \tau, \theta)$ is the vector of the parameters to be estimated. The parameters of the distance function can be estimated only if linear homogeneity in outputs is imposed. Following Coelli and Perelman (2000), all output quantities in the right-hand side of equation (15) are divided by the quantity of an arbitrary output, say the first output, as the numeraire. Let's denote $y_m^* = y_m/y_1$, and the translog function is rewritten as

$\mathrm{lnD}_{\mathrm{o}}^{\mathrm{t}}\left(x^t, \frac{y^t}{y_1^t}\right) = TL\left(x^t, \frac{y^t}{y_1^t}, t; \pi\right)$ and hence

$$-\ln(y_1^t) = TL(x^t, y_m^*, t; \pi) - ln\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{x}^{\mathrm{t}},\mathrm{y}^{\mathrm{t}}). \qquad (16)$$

Since $ln\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{x}^{\mathrm{t}},\mathrm{y}^{\mathrm{t}})$ is unobservable, setting $u^t = -ln\mathrm{D}_{\mathrm{o}}^{\mathrm{t}}(\mathrm{x}^{\mathrm{t}},\mathrm{y}^{\mathrm{t}})$ and adding a stochastic term v, one obtains the familiar production stochastic frontier

$$
\begin{aligned}
-lny_1^t &= TL(x^t, y^*, t; \pi) + u^t + v^t = \alpha_0 + \sum_{k=1}^{K}\alpha_k lnx_k^t + \sum_{m=2}^{M}\beta_m lny_m^{t\,*} \\
&+ \frac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K}\alpha_{kk'} lnx_k^t lnx_{k'}^t + \frac{1}{2}\sum_{m=2}^{M}\sum_{m'=2}^{M}\beta_{mm'} lny_m^{t\,*} lny_{m'}^{t\,*} \\
&+ \sum_{k=1}^{K}\sum_{m=2}^{M}\gamma_{km} lnx_k^t lny_m^{t\,*} + \sum_{k=1}^{K}\delta_{kt} lnx_k^t t + \sum_{m=2}^{M}\tau_{mt} lny_m^{t\,*} t + \theta_t t + \frac{1}{2}\theta_{tt}t^2 \\
&+ u^t + v^t, \qquad (17)
\end{aligned}
$$

where u represents the stochastic shortfall of the production unit's output from the production frontier due to technical inefficiency, u is a random nonnegative error term, and v is a symmetric and normally distributed error term of $N(0, \sigma_v^2)$. Both error terms are independently distributed. Identification of the inefficiency stochastic term requires some structure to be placed on the heterogeneous and temporal pattern of technical efficiency. Following Battese and Coelli (1995), the stochastic term u_{it} is defined as a normally distributed variable $N(\mu_{it}; \sigma_u^2)$ truncated at zero.

$$\mu_{it} = z_{it}\varphi, \tag{18}$$

where z_{it} is a vector of observable explanatory variables and φ is a vector of parameters to be estimated. The predicted value of the output distance function can be estimated as a conditional expectation:

$$\mathrm{D_o^t(x^t, y^t)} = E[\exp(-u^t)\,|\varepsilon^t] = \frac{1-\Phi(\sigma_A - \chi\varepsilon^t/\sigma_A)}{1-\Phi(\chi\varepsilon^t/\sigma_A)}\exp(\chi\varepsilon^t + \sigma_A^2/2), \tag{19}$$

where $\varepsilon^t = u^t + v^t, \sigma^2 = \sigma_u^2 + \sigma_v^2, \chi = \frac{\sigma_u^2}{\sigma^2}, \sigma_A = \sqrt{\chi(1-\chi)\sigma^2}$ and Φ represents a standard normal distribution function.

Once the parameters of equation (17) are estimated, the assembling parts of the Malmquist productivity index and its components can be calculated (Balk 2001; Fuentes, Grifell-Tatje, and Perelman 2001).
Technical change magnitude:

$$\begin{aligned}\mathrm{TCM} = \frac{\mathrm{D_o^t(x^t, y^t)}}{\mathrm{D_o^{t+1}(x^t, y^t)}} &= \exp\left[TL\left(x^t, y_m^{t\,*}, t; \hat{\pi}\right) - TL\left(x^t, y_m^{t\,*}, t+1; \hat{\pi}\right)\right] \\ &= \exp\left\{(-1) \times \left[\textstyle\sum_{k=1}^{K} \hat{\delta}_{kt} lnx_k^t + \sum_{m=2}^{M} \hat{\tau}_{mt} lny_m^{t\,*} + \hat{\theta}_t + \hat{\theta}_{tt}\left(t + \frac{1}{2}\right)\right]\right\}.\end{aligned} \tag{20}$$

Output bias index:

$$\begin{aligned}\mathrm{OB} = \exp\Big\{\tfrac{1}{2} \times \Big[&TL\left(x^{t+1}, y_m^{t+1^*}, t; \hat{\pi}\right) - TL\left(x^{t+1}, y_m^{t+1^*}, t+1; \hat{\pi}\right) + TL\left(x^{t+1}, y_m^{t\,*}, t+1; \hat{\pi}\right) - \\ &- TL\left(x^{t+1}, y_m^{t\,*}, t; \hat{\pi}\right)\Big]\Big\} = exp\left\{\tfrac{1}{2} \times \left[\textstyle\sum_{m=2}^{M} \hat{\tau}_{mt}(lny_m^{t\,*} - lny_m^{t+1^*})\right]\right\}.\end{aligned} \tag{21}$$

Input bias index:

$$\begin{aligned}\mathrm{IB} = \exp\Big\{\tfrac{1}{2} \times \Big[&TL\left(x^{t+1}, y_m^{t\,*}, t; \hat{\pi}\right) - TL\left(x^{t+1}, y_m^{t\,*}, t+1; \hat{\pi}\right) + TL\left(x^t, y_m^{t\,*}, t+1; \hat{\pi}\right) - \\ &- TL\left(x^t, y_m^{t\,*}, t; \hat{\pi}\right)\Big]\Big\} = exp\left\{\tfrac{1}{2} \times \left[\textstyle\sum_{k=1}^{K} \hat{\delta}_{kt}(lnx_k^t - lnx_k^{t+1})\right]\right\}.\end{aligned} \tag{22}$$

Efficiency change:

$$\mathrm{EC} = \exp\left\{TL\left(x^{t+1}, y_m^{t+1^*}, t+1; \hat{\pi}\right) - TL\left(x^t, y_m^{t\,*}, t; \hat{\pi}\right)\right\}. \tag{23}$$

Balk (2001) showed that the SEC and OME can be computed by using estimates of the output-oriented scale efficiency without estimating the output distance function under constant returns to scale, as required in the nonparametric approach. For any arbitrary pair $(\bar{x}, \bar{y})$ the output-oriented measure of scale efficiency of a translog distance function is

$$lnOSE^t(\bar{x}, \bar{y}) = -\frac{[\epsilon_o^t(\bar{x}, \bar{y}) - 1]^2}{2\alpha^t}, \tag{24}$$

where the scale elasticity

$$\epsilon_o^t(\bar{x},\bar{y}) = \sum_{k=1}^{K} \frac{\partial ln \mathrm{D}_\mathrm{o}^\mathrm{t}(\bar{x},\bar{y})}{\partial lnx_k} = \sum_{k=1}^{K}\left[\hat{\alpha}_k + \sum_{k'=1}^{K} \hat{\alpha}_{kk'} lnx_{k'}^t + \sum_{m=2}^{M} \hat{\gamma}_{km} lny_m^{t\,*} + \sum_{k=1}^{K} \hat{\delta}_{kt} t\right], \quad (25)$$

and $\alpha^t = \sum_{k=1}^{K} \sum_{k'=1}^{K} \hat{\alpha}_{kk'}$.

Since local scale efficiency can never exceed the optimal scale efficiency, $OSE^t(\bar{x},\bar{y}) \leq 1$, which requires that $\alpha^t > 0$. Equation (25) indicates that the output-oriented scale efficiency of a particular input-output combination can be obtained from the output distance function–based measure of local scale elasticity ϵ pertaining to this combination, and ϵ can be evaluated at any data point from the parameter estimates of the output distance function.

Scale efficiency change:

$$SEC = exp\left\{\frac{1}{2} \times \left[-\frac{\left[\epsilon_o^t(x^{t+1},y^t)-1\right]^2}{2\alpha^t} + \frac{\left[\epsilon_o^t(x^t,y^t)-1\right]^2}{2\alpha^t} - \frac{\left[\epsilon_o^{t+1}(x^{t+1},y^{t+1})-1\right]^2}{2\alpha^t} + \frac{\left[\epsilon_o^{t+1}(x^t,y^{t+1})-1\right]^2}{2\alpha^t}\right]\right\}. \quad (26)$$

Output-mix effect:

$$OME = exp\left\{\frac{1}{2} \times \left[-\frac{\left[\epsilon_o^t(x^{t+1},y^{t+1})-1\right]^2}{2\alpha^t} + \frac{\left[\epsilon_o^t(x^{t+1},y^t)-1\right]^2}{2\alpha^t} - \frac{\left[\epsilon_o^{t+1}(x^t,y^{t+1})-1\right]^2}{2\alpha^t} + \frac{\left[\epsilon_o^{t+1}(x^t,y^t)-1\right]^2}{2\alpha^t}\right]\right\}. \quad (27)$$

Thus, all the assembling components of the Malmquist index can be computed from evaluation of the translog output distance function.

4. DATA

A panel of province-level data is collected for 31 provinces, municipal cities, and autonomous regions from the *China Statistical Yearbook* (China, National Bureau of Statistics, various years). There are four subsectors within agriculture: crop, livestock, fishery, and forestry. The subsector outputs are valued at constant 2010 billion yuan. Four major agricultural inputs are included: area, labor, machinery, and fertilizer. Area is defined as the total sown area in 1,000 hectares, labor measures rural employment in 10,000 persons, machinery measures agricultural machinery in 10,000 kilowatts hours, fertilizer is the consumption of chemical fertilizer in 10,000 metric tons. Although infrastructure and market structure do not directly contribute to output growth, they can affect production through improvement in productivity and its components. Rural infrastructure is proxied by the share of irrigated area in the crop sown area. Agricultural policies include market openness and taxation. Market openness is calculated as the value share of agricultural products whose prices are not directly managed or stipulated by the government. Taxation is the average rate of net agricultural tax (agricultural tax minus subsidies) per hectare of crop sown area. Dummies are introduced to capture unique biophysical conditions in the province.

Zhang and Brummer (2011) provide a comprehensive review of policy reform in China from 1978 to 2010, breaking it into six stages. In the first reform stage of decentralization (1978–1983), the government procurement quotas were reduced and some commodities were phased out of the procurement programs to be traded in markets. Agricultural output grew sharply in this period after the establishment of a household responsibility system. In the second stage of marketing system liberalization (1984–1989), although more products were liberalized the government maintained control over strategic products (grain, cotton, and oilcrops). A rapid increase in input prices dampened farmers' investment in agriculture and resulted in lower output growth. In the third stage, 1989–1993, reform in the grain-marketing system further cut the number of commodities subject to state procurement programs, but regional markets remained segmented due to various price and quantity controls for strategic crops. Increased procurement prices characterized the fourth stage, 1994–1999, spurring a fast expansion in agricultural output. In the fifth stage, 1998–2003, the grain procurement quota was abolished and a free grain market was applied to the majority of China. In the sixth stage, 2003–2010, the government shifted its focus from taxing agriculture to supporting producers with policies including input subsidies, direct payments, and agricultural tax reform.

Despite fluctuations and the shifting policy focus, agricultural production exhibited impressive growth since reform started. The output of the agricultural sector increased exponentially after reform, as the average annual growth rate reached nearly 6 percent during the 1978–2010 period (Table 4.1). Although crop production rose at 4.3 percent annually, it was dwarfed by the surge of high-value and nutritional animal products in the livestock and fishery sectors, which grew at 8.6 and 13 percent, respectively. The structure of input usage also shifted substantially, with modern inputs including machinery and fertilizer growing at a faster pace than traditional inputs like land and labor. Given land scarcity, rapid urbanization, and economic transformation in the country, it is not surprising that land barely expanded and labor engaged in rural activities increased by less than 2 percent per year. On the other hand, input intensification is widely observed since new machines serving agricultural production grew by 6.3 percent and total fertilizer consumption increased by nearly five times within three decades.

In terms of regional distribution, the highest agricultural output growth is observed in Xinjiang in the northwest, followed by Hainan, Inner Mongolia, and Henan, all driven by rapidly developing crop and other sectors. We observe increased modern inputs in those provinces, as well as land expansion in the relatively low-population-density regions. On the other hand, low agricultural growth occurred in highly urbanized municipalities (Beijing and Shanghai) or provinces facing adverse biophysical conditions (Xizang and Qinghai). Slow growth in input use was widespread in those provinces as well.

Table 4.1—Descriptive statistics

	Mean	Std. Err.	Annual growth rate (%)						
			1978–83	1984–89	1990–93	1994–97	1998–2003	2004–10	1978–2010
Output (billion 2009 yuan)									
Crop	99.5	64.1	9.0	-0.2	0.5	5.0	1.6	9.1	4.5
Livestock	60.8	45.7	12.4	10.9	3.8	6.1	6.1	7.1	8.5
Forestry	6.1	3.7	13.1	-1.8	3.9	1.3	6.6	9.3	4.8
Fishery	17.8	19.8	15.1	19.1	17.2	10.8	5.5	6.6	12.7
Input									
Area (in 1,000 hectare)	7105	3246	-0.9	0.3	-0.2	1.3	-0.4	0.6	0.3
Labor (in 10,000 person)	2323	1210	2.7	2.6	1.8	1.1	1.1	1.1	1.7
Machinery (in 10,000 kwh)	3005	2714	8.3	7.7	3.4	7.9	5.9	6.4	6.3
Fertilizer (in 10,000 metric ton)	214	136	12.3	6.2	6.5	5.9	1.6	3.2	5.3
Infrastructure and policy			0.0	0.0	0.0	0.0	0.0	0.0	0.0
Electricity (kwh per hectare)	307.5	520.7	3.3	11.7	14.2	10.6	11.0	8.9	10.2
Irrigation (% of cropland)	36.6	12.7	-0.2	0.2	1.0	1.8	0.4	1.8	1.0
Market openness (% of ag. value)	86.7	20.2	13.9	16.3	20.8	0.6	2.6	-0.1	8.6
Tax rate (yuan per hectare)	0.23	3.19	0.3	-0.3	0.0	2.8	6.6	-31.0	-2.6

Source: Authors' calculation based on data from *China Statistical Yearbook* (China, National Bureau of Statistics, various years).
Note: kwh = kilowatt hours.

5. EMPIRICAL RESULTS AND DISCUSSION

Before reporting the estimated productivity growth, we need to check whether the translog functional form is suitable for the study.

Curvature Condition

We first check whether the curvature condition is satisfied. O'Donnell and Coelli (2005) provide the general regularity properties for output distance functions: monotonicity (nondecreasing in outputs and nonincreasing in inputs), homogeneity of degree 1 in outputs, convexity in outputs, and quasi-convexity in inputs.

Monotonicity and curvature conditions involve constraints on functions of the partial derivatives of the distance function. The elasticity of distance with respect to input *k* and output *m* is

$$\epsilon_k^t(x,y) = \frac{\partial ln \mathrm{D_o^t}(x,y)}{\partial ln x_k} = \hat{\alpha}_k + \sum_{k'=1}^{K} \hat{\alpha}_{kk'} ln x_{k'}^t + \sum_{m=2}^{M} \hat{\gamma}_{km} ln y_m^{t\,*} + \sum_{k=1}^{K} \hat{\delta}_{kt} t, \text{ k = 1,…,K} \quad (28)$$

and

$$\epsilon_m^t(x,y) = \frac{\partial ln \mathrm{D_o^t}(x,y)}{\partial ln y_m^*} = \hat{\beta}_m + \sum_{m'=2}^{M} \hat{\beta}_{mm'} ln y_m^{t\,*} + \sum_{m=2}^{M} \hat{\gamma}_{km} ln x_k^t ln y_m^{t\,*} + \hat{\tau}_{mt} t, \text{ m = 2,…,M} \quad (29)$$

For the output distance function to be nonincreasing in input *k,*

$$f_k = \frac{\partial \mathrm{D_o^t}(x,y)}{\partial x_k} = \frac{\partial ln \mathrm{D_o^t}(x,y)}{\partial ln x_k} \frac{\mathrm{D_o^t}(x,y)}{x_k} = \epsilon_k^t(x,y) \frac{\mathrm{D_o^t}(x,y)}{x_k} \leq 0 \Leftrightarrow \epsilon_k^t(x,y) \leq 0, \text{ k = 1,…,K,} \quad (30)$$

because distance functions are positive by definition and input quantities are positive.

For the output distance function to be nondecreasing in output *m,*

$$h_m = \frac{\partial \mathrm{D_o^t}(x,y)}{\partial y_m^*} = \frac{\partial ln \mathrm{D_o^t}(x,y)}{\partial ln y_m^*} \frac{\mathrm{D_o^t}(x,y)}{y_m^*} = \epsilon_m^t(x,y) \frac{\mathrm{D_o^t}(x,y)}{y_m^*} \geq 0 \Leftrightarrow \epsilon_m^t(x,y) \geq 0, \text{ m = 2,…,M.} \quad (31)$$

Evaluated at the sample mean, the elasticities of the output distance function with respect to input quantities are -0.12 for land, -0.44 for labor, -0.07 for machinery, and -0.34 for fertilizer. This reflects the relative importance of labor and fertilizer in the production process. Moreover, the elasticities with respect to outputs indicate the share of each product in production improvement: livestock has the highest impact (0.26) compared with fishery (-0.03) or forestry (0.07). The negative values of the input elasticities indicate that the estimated output distance function is decreasing in all four inputs. Similarly, the distance function is found to be increasing in three out of four outputs based on their elasticities.

The output distance function is quasi-convexity in inputs if and only if the bordered Hessian matrix is negative definite. The Hessian matrix of inputs is

$$H_{input} = \begin{bmatrix} 0 & f_1 & \cdots & f_K \\ f_1 & f_{11} & \cdots & f_{1K} \\ \vdots & \vdots & \ddots & \vdots \\ f_K & f_{1K} & \cdots & f_{KK} \end{bmatrix},$$

where

$$= \frac{\partial^2 \mathrm{D}}{\partial x_k \partial x_{k'}} = \frac{\partial f_k}{\partial x_{k'}} = \frac{\partial(\epsilon_k D / x_k)}{\partial x_{k'}} = (\, \hat{\alpha}_{kk'} + \epsilon_k \epsilon_{k'} - \xi_{kk'} \epsilon_k)(\frac{D}{x_k x_{k'}}), \quad (32)$$

and $\xi_{kk'} = 1$ if $k = k'$ and 0 otherwise.

The output distance function is convex in output if and only if the Hessian matrix of outputs is positive definite.

$$H_{output} = \begin{bmatrix} h_{21} & \cdots & h_{2M} \\ \vdots & \ddots & \vdots \\ h_{2M} & \cdots & h_{MM} \end{bmatrix},$$

where

$$h_{mm'} = \frac{\partial^2 \mathrm{D}}{\partial y_m^* \partial y_{m'}^*} = \frac{\partial h}{\partial y_{m'}^*} = \frac{\partial(\epsilon_m D / y_m)}{\partial y_{m'}^*} = (\,\hat{\beta}_{mm'} + \epsilon_m \epsilon_{m'} - \xi_{mm'} \epsilon_m)(\frac{D}{y_m^* y_{m'}^*}), \tag{33}$$

and $\xi_{mm'} = 1$ if $m = m'$ and 0 otherwise.

The Hessian matrix of inputs is found to be negative semidefinite, and two out of three eigenvalues of the output Hessian matrix are positive. These results confirm that the quasi-convexity in inputs of the estimated function is satisfied, but convexity in outputs is only partially satisfied.

Parameter Estimates and Hypotheses Tests

Parameter estimates of the translog output distance function from the maximum likelihood procedure are summarized in Table 5.1. The variance parameters are statistically significant at the 1 percent level, and the ratio of σ_u^2 in total variance is estimated at 0.687.

Table 5.1—Results of hypotheses tests

Hypothesis	Log-likelihood Ratio statistic	P-value
Mean distance function	388.0	0.000
No heterogeneous technical inefficiency	388.0	0.000
Input Hicks neutral	9.4	0.024
Output Hicks neutral	13.7	0.056
Input and output Hicks neutral	159.7	0.000
No technical change	2.9	0.567
Input-output separability	104.8	0.000
Cobb-Douglas functional form	429.3	0.000
Constant returns to scale	128.2	0.000

Source: Authors' calculation.

The parametric approach permits formal testing of the statistical significance of various sources of productivity changes. Alternative model specifications can be evaluated using likelihood ratio tests, which compare the likelihood functions under the null and alternative hypotheses based on the translog output distance function defined earlier.

First we compare the frontier with the mean output distance function, estimated by considering the inefficiency term u as nonstochastic and equal to zero. Any deviation from the production frontier is interpreted as random error, and the distance function can be estimated using ordinary least squares. This assumption translates into the parameter restriction of

$$\chi = \mu = \varphi_0 = \varphi_{Dummy} = \varphi_1 = \varphi_2 = \varphi_3 = 0. \tag{34}$$

The technical inefficiency exists because the null hypothesis is rejected at the 1 percent level (Table 5.2). This is confirmed by the significantly large value of parameter χ in Table 5.1 (388.0), indicating that more than two-thirds of the output variability can be explained by technical inefficiency, rather than random shocks.

Table 5.2—Parameter estimates of the translog output distance function

Parameter	Parameter	Estimate	Std. err.	Parameter	Estimate	Std. err.
β_1	lny1	-0.575	(0.437)	γ_{22}	-0.026	(0.027)
β_2	lny2	-0.617	(0.150)***	γ_{23}	0.016	(0.036)
β_3	lny3	0.798	(0.163)***	γ_{31}	0.061	(0.052)
α_1	lnx1	0.862	(0.629)	γ_{32}	-0.021	(0.016)
α_2	lnx2	-3.242	(0.352)***	γ_{33}	0.091	(0.031)***
α_3	lnx3	0.079	(0.422)	γ_{41}	-0.228	(0.067)***
α_4	lnx4	1.293	(0.535)**	γ_{42}	-0.002	(0.026)
β_{11}	lny1y1	0.061	(0.089)	γ_{43}	0.148	(0.034)***
β_{12}	lny1y2	0.082	(0.015)***	τ_{1t}	0.008	(0.005)*
β_{13}	lny1y3	0.010	(0.030)	τ_{2t}	-0.001	(0.002)
β_{22}	lny2y2	-0.030	(0.008)***	τ_{3t}	-0.004	(0.003)*
β_{23}	lny2y3	-0.032	(0.012)***	δ_{1t}	-0.019	(0.009)**
β_{33}	lny3y3	0.042	(0.020)**	δ_{2t}	0.015	(0.006)***
α_{11}	lnx1x1	-0.425	(0.181)**	δ_{3t}	-0.002	(0.005)
α_{12}	lnx1x2	0.497	(0.106)***	δ_{4t}	0.008	(0.007)
α_{13}	lnx1x3	-0.094	(0.105)	θ_t	0.029	(0.038)
α_{14}	lnx1x4	-0.018	(0.108)	θ_{tt}	-0.002	(0.001)***
α_{22}	lnx2x2	-0.314	(0.095)***	α_0	4.313	(1.802)**
α_{23}	lnx2x3	0.205	(0.081)**			
α_{24}	lnx2x4	-0.212	(0.077)***	φ_1	0.011	(0.017)
α_{33}	lnx3x3	-0.098	(0.077)	φ_2	-0.007	(0.005)
α_{34}	lnx3x4	0.037	(0.072)	φ_3	-0.188	(0.051)***
α_{44}	lnx4x4	-0.050	(0.091)	φ_0	-3.725	(0.750)***
γ_{11}	lny1x1	0.304	(0.086)***			
γ_{12}	lny2x1	0.099	(0.032)***	$ln\sigma_v^2$	-4.247	(0.074)***
γ_{13}	lny3x1	-0.241	(0.043)***	χ	0.687	
γ_{21}	lny1x2	-0.132	(0.061)**	log likelihood	493.9	

Source: Authors' calculation.

Note: For outputs, 1 stands for livestock, 2 for fishery, and 3 for forestry. For inputs, 1 stands for area, 2 for labor, 3 for machinery, and 4 for fertilizer. For inefficiency terms, 1 stands for share of irrigation, 2 stands for market openness, and 3 stands for agricultural tax. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In addition, we want to test whether the variables introduced as inefficiency effects improve the explanatory power of the model. The null hypothesis is reduced as

$$\varphi_{Dummy} = \varphi_1 = \varphi_2 = \varphi_3 = 0. \tag{35}$$

The null hypothesis is firmly rejected at 1 percent, indicating that the distribution of inefficiencies is not identical across individual observations but depends on the variables capturing local natural endowment and policies. This test supports the heterogeneity of the inefficiency term.

The second set of hypotheses concerns technology bias and technical change by checking the parameters used for the OB, IB, and TCM calculations. For the production technology to be implicit Hicks neutral in inputs and make no contribution to productivity growth, the input bias index IB = 1, lnIB = 0. That means to test parameters,

$$\delta_{kt} = 0, \text{ for all } k = 1,\ldots,K. \tag{36}$$

Similarly, the test for implicit Hicks neutrality in outputs, OB = 1, or lnOB = 0, is

$$\tau_{mt} = 0, \text{ for all } m = 1,\ldots,M. \quad (37)$$

No technology bias is a combination of the two tests above.

If there is no change in the technical change magnitude, TCM = 1, or lnTCM = 0, requiring us to jointly test the parameters

$$\delta_{kt} = \tau_{mt} = \theta_t = \theta_{tt} = 0, \text{ for all k} = 1,\ldots,\text{K and m} = 1,\ldots,\text{M}. \quad (38)$$

Hence, no technical change, or TC = 1, is the equivalent of a joint test of the significance of equations (36), (37), and (38).

The hypothesis of input Hicks neutrality cannot be rejected, and output Hicks neutrality is rejected at the 5 percent level, resulting in a marginal rejection of technology bias. The joint test result implies that technical change is present.

Separability of outputs is an important property of production. It implies that marginal rates of substitution between pairs of outputs in the separated group are independent of the levels of outputs outside the group; hence outputs can be aggregated in the analysis.

The hypothesis of separability is defined as all interaction terms between outputs and inputs being zero:

$$\gamma_{km} = 0, \text{ for all } k = 1,\ldots,K \text{ and } m = 1,\ldots,M. \quad (39)$$

These restrictions on parameters are strongly rejected, which shows that it is not possible to aggregate the four outputs consistently into a single index. This again demonstrates the strength of the distance function compared with a traditional stochastic frontier production function, which requires aggregation of outputs prior to model estimation, as revealed by Alene, Manyong, and Gockowski (2006). Then we test whether the true output distance function can be simplified and represented by the Cobb-Douglas functional form instead of the translog form. The parameter restrictions are

$$\alpha_{kk'} = \beta_{mm'} = \gamma_{km} = \delta_{kt} = \tau_{mt} = 0, \text{ for all k} = 1,\ldots,\text{K and m} = 1,\ldots,\text{M}. \quad (40)$$

The null is rejected, suggesting that the Cobb-Douglas form is inappropriate for this study.
The last hypothesis is the constant returns to scale, which requires the output distance function to be homogenous of degree -1 in input quantities (Coelli and Perelman 2000), or the following restrictions should hold:

$$\sum_{k=1}^{K} \alpha_k = -1, \sum_{k'=1}^{K} \alpha_{kk'} = 0, \sum_{k=1}^{K} \gamma_{km} = 0, \sum_{k=1}^{K} \delta_{kt} = 0, \text{ for all k} = 1,\ldots,\text{K and m} = 1,\ldots,\text{M}. \quad (41)$$

The hypothesis of constant returns to scale is rejected as well, suggesting that the component of scale inefficiency should be considered in measuring productivity change.

Following Färe and Primont (1995), returns to scale can be computed from the output distance function as follows:

$$\varepsilon(x^t, y^t) = -\left(\sum_{k=1}^{K} \frac{\partial lnD_o^t(x^t,y^t)}{\partial lnx_k^t}\right).$$

The expression in brackets is the proportional increase in all outputs caused by an increase in all inputs in the same proportion. Therefore, increasing (decreasing) returns to scale are indicated by a value of returns to scale greater (less) than one.

The mean returns to scale is 0.967. The null hypothesis of constant returns to scale against the alternative hypothesis of decreasing returns to scale is strongly rejected, suggesting a decreasing returns to scale is appropriate to describe the production technology.

TFP Change and Its Components

First we look at technical efficiency. The average technical efficiency is 0.884 despite more efficient production in the mid-1990s to the early 2000s. In terms of regional distribution, the northern and central regions report the highest efficiency score, where agricultural production is encouraged by favorable biophysical conditions and policy support (Table 5.3). Technical efficiency is the lowest in the northeast region, with an average technical efficiency index of 0.76. The low efficiency score means that with the same amount of inputs the low-performing provinces can increase the level of outputs by about 50 percent (appendix Table A.1). The sharp drop in technical efficiency since 2004 is especially alarming; it was caused by several weather shocks and the outbreak of animal diseases in northeastern and southern China, where pork production is concentrated.

Table 5.3—Technical efficiency in China

Region	1978–83	1984–89	1990–93	1994–97	1998–2003	2004–10	1978–2010
North	0.948	0.898	0.896	0.921	0.947	0.954	0.938
Northeast	0.808	0.784	0.822	0.796	0.772	0.714	0.757
Central	0.901	0.893	0.94	0.94	0.957	0.920	0.928
South	0.859	0.848	0.881	0.918	0.924	0.862	0.882
Southwest	0.897	0.877	0.891	0.902	0.896	0.781	0.850
West	0.898	0.824	0.823	0.816	0.859	0.842	0.842
China	0.884	0.865	0.894	0.906	0.916	0.863	0.884

Source: Authors' calculation.

We expect rural infrastructure, market openness, and agricultural support to improve technical efficiency. The coefficients of market openness and real agricultural support are both of the expected sign, but only the latter is statistically significant (Table 5.2). Combined with the significant constant term in technical inefficiency variables, we confirm not only the existence of technical inefficiency, but also the positive role of agricultural policy in improving technical efficiency.

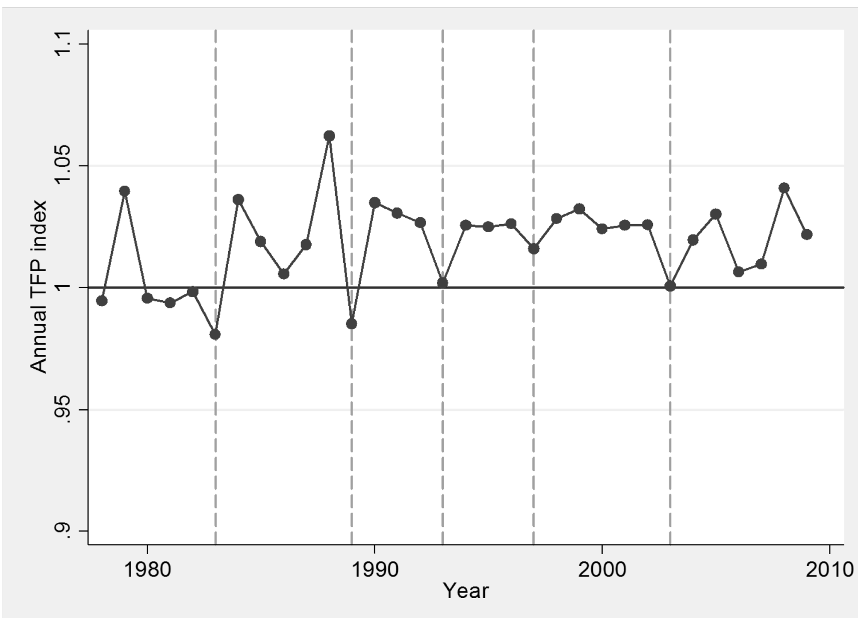
Table 5.4 summarizes the parametric estimation of the Malmquist index and its components, and Figure 5.1 reports the annual TFP growth of the country. It is clear that the development of productivity matches the six stages of reform as described in the data. With the exception of some years at the early stages of reform, the annual TFP growth index is above unity, suggesting productivity improvement over time. During the period 1978–2010, the average agricultural productivity growth rate is about 2 percent per year. After the first stage of reform in 1978–1983, agricultural TFP maintains a steady growth rate of more than 2 percent per year (appendix Table A.2). That growth rate is similar to the finding of Nin-Pratt, Yu, and Fan (2009) but lower than that of Zhang and Brummer (2011).

Table 5.4—Decomposition of Malmquist productivity index

Period	1978–83	1984–89	1990–93	1994–97	1998–2003	2004–10	1978–2004
Productivity (TFP)	0.999	1.021	1.023	1.023	1.022	1.022	1.020
Technical efficiency change (EC)	0.991	1.010	1.007	1.004	0.998	0.989	0.997
Technical change (TC)	1.008	1.011	1.015	1.018	1.025	1.032	1.023
Technical change magnitude (TCM)	1.009	1.012	1.015	1.018	1.025	1.033	1.024
Output bias (OB)	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Input bias (IB)	0.999	1.000	1.000	1.000	1.000	1.000	1.000
Scale efficiency change (SEC)	1.000	1.000	1.001	1.001	1.000	1.001	1.001
Output-mix effect (OME)	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Source: Authors' calculation.

Figure 5.1—Evolution of TFP over time



Source: Authors' calculation.

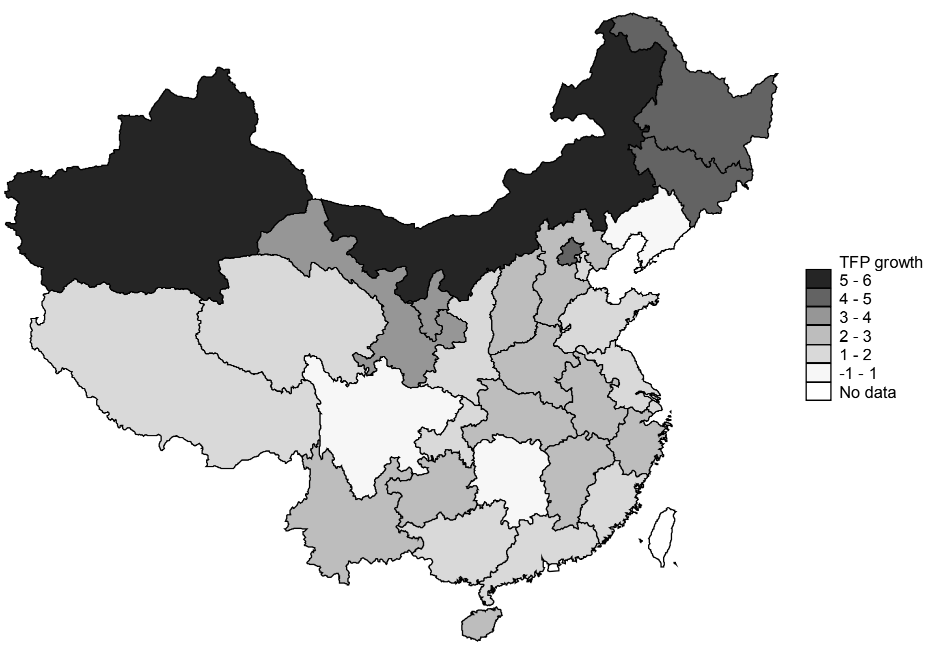
The overall TFP development can be explained by the components of the Malmquist index, namely, technical change and bias, technical efficiency change, scale efficiency change, and output-mix effect. The technical efficiency change is less than 1 for the whole period, implying deteriorated technical efficiency. However, technical efficiency rises from 1984 to 1997, and declines afterward. This decline is most pronounced after 2004, further highlighting the urgent need for efficiency improvement.

Technical change, at 2.3 percent growth per year, is the main driving force of productivity growth in China. In addition, technical change exhibits an accelerated pattern over time: the average technical change rate increases from 0.8 percent per annum in 1978–1983 to 3.2 percent in 2004–2010. Table 5.4 also shows the decomposition of the technical change component into the production of technical change along a ray through the data of each period (TCM) and the bias effect. Although statistically significant, the impact of output bias on productivity is very small. Since both input and output bias indexes are close to 1, neither an input bias effect nor an output bias effect has occurred during the period of study and we conclude that the technical change is Hicks neutral. In other words, there is a globally neutral shift in the production frontier and technical change does not have much influence in the relative contribution of each output or input to the production process. Therefore, a productivity gain cannot be obtained by changing the mix of outputs or the mix of inputs, and current technology does not favor an output and input mix from different periods. This results in a wide distribution of input and output combinations in Chinese agriculture.

Scale efficiency boosts the Malmquist index by a small margin (average SEC is 1.001), which implies that the output mix moves closer to the technical optimal and scale efficiency improves over time. Together with the output bias, we observe that the mix of outputs is closer to the optimal mix of outputs under the technology as SEC averages 1.001. In relatively land-abundant northern China, scale efficiency improves because the output mix is moving closer to the optimal production technology. There is little change in the output-oriented scale efficiency from a change in the output mix, and hence OME does not contribute to productivity growth.

Figure 5.2 and Table 5.5 show the spatial distribution of agricultural productivity. The highest TFP growth is observed in the northern and northwestern border provinces of Xinjiang and Inner Mongolia at more than 5 percent per annum, partly due to the rapid growth of the crop and livestock sectors. The northern provinces of Heilongjiang and Jilin follow suit by reporting an impressive TFP growth rate of between 4 and 5 percent. Gansu and Ningxia, two inland provinces in north China, also benefit from the boom in the agricultural sectors in the neighborhood. On the other hand, the provinces exhibiting low productivity growth include Sichuan, Liaoning, and Hunan, mainly caused by efficiency deterioration with efficiency scores dropping at more than 1 percent per year.

Figure 5.2—Map of annual productivity growth



Source: Authors' calculation.

Table 5.5—Decomposition of Malmquist productivity index by region

Region	Indexes	1978–83	1984–89	1990–93	1994–97	1998–2003	2004–10	1978–2010
North	TC	1.014	1.017	1.020	1.021	1.027	1.034	1.026
	EC	0.990	0.999	1.000	1.012	0.998	1.006	1.003
	SEC	1.001	0.998	1.000	1.001	1.000	1.002	1.001
	TFP	1.005	1.015	1.020	1.034	1.025	1.042	1.030
Northeast	TC	1.025	1.025	1.026	1.029	1.034	1.042	1.034
	EC	0.978	1.031	1.002	0.989	0.999	0.985	0.994
	SEC	1.006	1.001	1.003	0.999	1.001	1.002	1.002
	TFP	1.007	1.056	1.031	1.016	1.033	1.029	1.029
Central	TC	1.004	1.008	1.012	1.016	1.024	1.031	1.021
	EC	0.997	1.011	1.002	1.005	1.000	0.991	0.999
	SEC	0.999	0.999	1.001	1.001	1.000	1.001	1.000
	TFP	1.000	1.019	1.015	1.022	1.024	1.023	1.020
South	TC	1.008	1.010	1.013	1.016	1.022	1.028	1.020
	EC	0.993	1.012	1.018	1.004	0.997	0.983	0.996
	SEC	1.000	1.000	1.001	1.001	1.000	1.001	1.000
	TFP	1.000	1.022	1.032	1.021	1.018	1.011	1.016
Southwest	TC	1.000	1.004	1.009	1.013	1.021	1.029	1.017
	EC	0.984	1.008	1.009	1.000	0.987	0.986	0.993
	SEC	0.999	0.999	0.999	1.000	1.000	1.000	1.000
	TFP	0.983	1.012	1.017	1.013	1.008	1.014	1.010
West	TC	1.018	1.022	1.024	1.026	1.033	1.040	1.031
	EC	0.987	0.994	1.004	1.017	1.007	0.990	0.999
	SEC	1.002	1.002	1.004	1.004	1.000	1.004	1.003
	TFP	1.006	1.016	1.032	1.048	1.041	1.035	1.033

Source: Authors' calculation.
Note: TC = technical change; EC = technical efficiency change; SEC = scale efficiency change; TFP = total factor productivity.

It is important to examine the distribution of technical change and efficiency change given their key role in TFP growth. Similar to the pattern of TFP growth, the northern provinces move closer to the production frontier represented by provinces reporting that technical efficiency equals 1 (Hebei, Shanxi, Heilongjiang, Henan, and Guizhou). Low TC growth occurs in more urbanized municipalities and the coastal provinces of Jiangsu and Zhejiang where agriculture becomes a small player in the local economy. Efficiency improves in the northern provinces along with Hubei, while efficiency declines in provinces scoring low TFP growth like Liaoning, Hunan, and Sichuan.

Low and sharply declining efficiency scores are more pronounced in Liaoning, Hainan, and Sichuan, where output only reaches less than 70 percent of full potential, and annual technical efficiency indexes fall at an alarming rate of 2 to 4 percent per year. This is especially noticeable in Sichuan province, which is a major producer of agricultural commodities and contributed 6 percent of national agricultural production in 2010. Among the top five major agriculture-producing provinces, Sichuan is the only one that experienced negative TFP growth in 1978–2010, which may be due in part to the lack of rural infrastructure and unfavorable agricultural policies. Only 25 percent of the crop sown area is irrigated in Sichuan, far below the average of 40 percent. Sichuan also has a long history of high agricultural taxes, discouraging investment in the agricultural sector.

6. CONCLUSION

The paper uses an output-oriented parametric approach to extend the decomposition of the Malmquist productivity index suggested by Balk (2001) and Färe et al. (1997). The Malmquist index is decomposed into several assembling components, which allows us to examine the ray expansion of technology, input- and output-induced shifts of the technology frontier, technical change, scale efficiency change, and productivity change caused by the output mix. A translog output distance function is chosen to represent the production technology. A computable form of each component of the Malmquist index is expressed as a function of parameters estimable in the output distance function, and the Malmquist index is derived from those components.

The advantage of the parametric approach is the flexibility to statistically test hypotheses regarding the different components of the Malmquist index, the nature and the bias of the production technology, returns to scale, and the functional form by imposing restrictions on parameters. In addition, this paper differs from other studies by expressing results in a discrete-changes format, instead of derivatives. This is useful in empirical studies because most economic variables are not presented as continuous, and the estimated productivity growth index using first order derivatives can lead to incorrect results (Coelli, Rao, and Battese 1998; Pantzios, Karagianis, and Tzouvelekas 2011).

This paper presents an empirical study of TFP change in Chinese agriculture during the post-reform period of 1978–2010. The level of technical efficiency averages 0.884, with low efficiency scores in the north. The recent drop in technical efficiency is a reason for concern, suggesting insufficient rural infrastructure and a lack of supportive policies. On average, productivity grows at 2 percent per year—mostly driven by technical change. Additionally, the result of the decomposition of the technical change indicates that it is technology neutral despite the output mix moving closer to the technical optimal. Scale efficiency marginally contributes to productivity growth, whereas the output-mix effect is smaller. The findings have clear policy implications regarding improving agricultural performance in China. For example, past agricultural policies have failed to address China's huge efficiency gap so as to decrease wasteful use of agricultural inputs and cut down on environmental costs. Whether productivity can be improved through a shift in current technology is another relevant issue worth exploring. Additionally, given the considerable spatial variation, agricultural development policies need to be tailored to local conditions during planning and implementation. An important issue not discussed in this paper is future sources of productivity growth, including investment in agricultural research, rural education, and water.

APPENDIX: SUPPLEMENTARY TABLES

Table A.1—Malmquist productivity index and its components by province

Region	Province	TC	TCM	OB	IB	TE	EC	SEC	OME	TFP
North	Beijing	1.016	1.017	1.000	1.000	0.638	1.022	1.003	1.001	1.044
	Hebei	1.021	1.022	1.000	1.000	1.000	1.000	1.000	1.000	1.021
	Inner Mongolia	1.042	1.043	1.000	1.000	0.830	1.005	1.003	1.000	1.051
	Shanxi	1.029	1.030	1.000	1.000	1.000	1.000	1.000	1.000	1.029
	Tianjin	1.023	1.024	1.000	1.000	1.000	1.000	0.994	1.001	1.018
Northeast	Heilongjiang	1.047	1.048	1.000	1.000	1.000	1.000	1.003	0.999	1.049
	Jilin	1.032	1.033	1.000	1.000	0.678	1.007	1.003	0.999	1.041
	Liaoning	1.025	1.026	1.000	1.000	0.608	0.982	1.000	1.000	1.006
Central	Anhui	1.024	1.025	1.000	1.000	0.915	1.004	1.000	1.000	1.027
	Fujian	1.024	1.025	1.000	1.000	0.933	0.995	1.000	1.000	1.019
	Jiangsu	1.017	1.018	1.000	1.000	0.914	1.001	1.000	1.000	1.017
	Jiangxi	1.030	1.032	1.000	1.000	0.920	0.991	1.000	1.001	1.022
	Shandong	1.020	1.021	1.000	1.000	0.936	0.999	1.000	1.000	1.019
	Shanghai	1.010	1.011	1.000	1.000	1.000	1.000	1.001	1.001	1.012
	Zhejiang	1.019	1.020	1.000	1.000	0.937	1.000	1.001	1.001	1.021
South	Guangdong	1.014	1.015	1.000	1.000	0.869	0.998	1.000	1.000	1.012
	Guangxi	1.022	1.024	1.000	1.000	0.916	0.995	0.999	1.000	1.016
	Hainan	1.038	1.039	1.000	1.000	0.600	0.985	1.000	1.000	1.022
	Henan	1.019	1.020	1.000	1.000	1.000	1.000	1.002	1.000	1.021
	Hubei	1.023	1.025	1.000	1.000	0.859	1.005	1.000	1.000	1.029
	Hunan	1.022	1.023	1.000	1.000	0.778	0.982	1.000	1.000	1.003
Southwest	Chongqing	1.017	1.018	1.000	1.000	0.983	1.000	0.999	1.000	1.017
	Guizhou	1.020	1.021	1.000	1.000	1.000	1.000	1.000	1.000	1.020
	Sichuan	1.013	1.015	1.000	1.000	0.763	0.986	1.000	1.000	0.999
	Xizang	1.018	1.019	1.000	1.000	1.000	1.000	0.994	0.999	1.011
	Yunnan	1.025	1.027	1.000	1.000	0.870	0.999	0.999	1.000	1.024
West	Gansu	1.029	1.031	1.000	1.000	0.972	1.000	1.000	1.001	1.030
	Ningxia	1.038	1.039	1.000	1.000	1.000	1.000	1.000	1.000	1.038
	Qinghai	1.022	1.023	1.000	1.000	0.916	0.999	1.000	0.998	1.018
	Shaanxi	1.024	1.025	1.000	1.000	0.930	0.987	1.002	1.000	1.013
	Xinjiang	1.041	1.042	1.000	1.000	0.629	1.009	1.007	1.000	1.057
North		1.026	1.028	1.000	1.000	0.938	1.003	1.001	1.000	1.030
Northeast		1.034	1.035	1.000	1.000	0.757	0.994	1.002	0.999	1.029
Central		1.021	1.022	1.000	1.000	0.928	0.999	1.000	1.000	1.020
South		1.020	1.022	1.000	1.000	0.882	0.996	1.000	1.000	1.016
Southwest		1.017	1.019	1.000	1.000	0.850	0.993	1.000	1.000	1.010
West		1.031	1.033	1.000	1.000	0.842	0.999	1.003	1.000	1.033
China		1.023	1.024	1.000	1.000	0.884	0.997	1.001	1.000	1.020

Source: Authors' calculation.
Note: TC = technical change; TCM = technical change magnitude; OB = output bias; IB = input bias; TE = technical efficiency; EC = technical efficiency change; SEC = scale efficiency change; OME = output-mix effect; TFP = total factor productivity.

Table A.2—Malmquist productivity index and its components by year

Year	TC	TCM	OB	IB	TE	EC	SEC	OME	TFP
1978	1.008	1.009	1.000	0.999	0.892	0.989	0.998	1.000	0.995
1979	1.007	1.008	1.000	0.999	0.882	1.033	1.000	1.000	1.040
1980	1.008	1.008	1.000	1.000	0.904	0.987	1.002	1.000	0.996
1981	1.008	1.009	1.000	0.999	0.890	0.987	0.999	0.999	0.994
1982	1.009	1.009	1.000	0.999	0.877	0.988	1.001	1.001	0.998
1983	1.010	1.010	1.000	1.000	0.866	0.970	1.002	0.999	0.981
1984	1.011	1.011	0.999	1.000	0.841	1.026	1.000	0.999	1.036
1985	1.011	1.011	1.000	1.000	0.859	1.009	0.999	1.000	1.019
1986	1.012	1.012	1.000	1.000	0.864	0.994	0.999	1.000	1.006
1987	1.011	1.013	0.999	1.000	0.859	1.008	0.999	1.000	1.018
1988	1.011	1.012	1.000	1.000	0.863	1.051	1.000	1.000	1.062
1989	1.012	1.012	1.000	1.000	0.901	0.973	1.001	1.000	0.985
1990	1.013	1.014	1.000	1.000	0.874	1.021	1.001	1.000	1.035
1991	1.014	1.015	1.000	1.000	0.890	1.015	1.001	1.000	1.031
1992	1.015	1.016	1.000	1.000	0.902	1.009	1.002	1.000	1.027
1993	1.015	1.016	0.999	1.000	0.910	0.985	1.001	1.001	1.002
1994	1.016	1.016	1.000	1.000	0.896	1.008	1.001	1.000	1.026
1995	1.017	1.017	1.000	1.000	0.904	1.006	1.001	1.000	1.025
1996	1.019	1.019	1.000	1.000	0.908	1.007	1.001	0.999	1.026
1997	1.020	1.020	1.000	1.000	0.914	0.996	1.000	1.000	1.016
1998	1.022	1.022	1.000	1.000	0.909	1.008	0.999	1.000	1.028
1999	1.023	1.023	1.000	1.000	0.913	1.009	1.000	1.000	1.032
2000	1.024	1.024	1.000	1.000	0.920	1.000	1.001	1.000	1.024
2001	1.025	1.025	1.000	1.000	0.919	1.000	1.001	1.000	1.026
2002	1.026	1.027	1.000	1.000	0.919	0.998	1.001	1.001	1.026
2003	1.027	1.028	0.999	1.000	0.916	0.974	1.001	1.000	1.001
2004	1.028	1.028	1.000	1.000	0.894	0.991	1.001	1.000	1.020
2005	1.030	1.029	1.000	1.000	0.886	0.999	1.001	1.000	1.030
2006	1.031	1.032	1.000	1.000	0.885	0.975	1.002	0.999	1.006
2007	1.032	1.032	1.000	1.000	0.862	0.978	1.001	1.000	1.010
2008	1.034	1.033	1.001	1.000	0.844	1.006	1.001	1.000	1.041
2009	1.036	1.036	1.000	1.000	0.851	0.984	1.001	1.001	1.022
1978–83	1.008	1.009	1.000	0.999	0.884	0.991	1.000	1.000	0.999
1984–89	1.011	1.012	1.000	1.000	0.865	1.010	1.000	1.000	1.021
1990–93	1.015	1.015	1.000	1.000	0.894	1.007	1.001	1.000	1.023
1994–97	1.018	1.018	1.000	1.000	0.906	1.004	1.001	1.000	1.023
1998–2003	1.025	1.025	1.000	1.000	0.916	0.998	1.000	1.000	1.022
2004–10	1.032	1.033	1.000	1.000	0.863	0.989	1.001	1.000	1.022
1978–2010	1.023	1.024	1.000	1.000	0.884	0.997	1.001	1.000	1.020

Source: Authors' calculation.

Note: TC = technical change; TCM = technical change magnitude; OB = output bias; IB = input bias; TE = technical efficiency; EC = technical efficiency change; SEC = scale efficiency change; OME = output-mix effect; TFP = total factor productivity.

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