

Productivity Growth in China: Evidence from Chinese Provinces^{1,©}

Xiang Ao and Lilyan Fulginiti²

Abstract. Young (1995) estimated Total Factor Productivity (TFP) growth for Hong Kong, Taiwan, Singapore and South Korea. He reported moderate growth rates for these four regions. This means that rapid growth of GDP in these four economies is due mainly to fast increase of inputs. Young (2000) also estimated the TFP growth rate of China to be 1.4% per year during the period of 1978 to 1998. Similar to his claim for the four "Asian Tigers", he concluded that "the productivity performance of the non-agricultural economy (of China) during the reform period is respectable, but not outstanding."

China's real GDP grew at about 9% every year during that period. Is this extraordinary growth rate only due to factor accumulation? Or is it to a large degree due to improved efficiency and innovations? To answer this question, this study uses a panel dataset of real GDP, capital stock, and labor force for 30 provinces for 1978 to 1998 to estimate the TFP for the Chinese economy. Two approaches are used to estimate the aggregate production technology: a fixed-effects model and a stochastic frontier model. Our results are consistent across models indicating a TFP growth rate of 4.9% and 3.3% respectively. Both estimates are higher than Young's 1.9%. Our estimates also indicate that national average of TFP's contribution to GDP growth amount to 41.3% and 38.7%, respectively. Other results of interest indicate that capital has contributed more than labor to GDP growth and that technological change has been labor using.

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²Lilyan E. Fulginiti is Professor of Agricultural Economics at the University of Nebraska-Lincoln. E-mail: lfulginiti@unl.edu

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Xiang Ao and Lylian Fulginiti

1 Introduction

There is a debate in the literature about whether the "Asian Tigers", with their astonishing growing speeds, are catching up to the developed countries. Alwyn Young (1995) pointed out that "once one accounts for the dramatic rise in factor inputs, one arrives at estimated total factor productivity growth rates that are closely approximated by the historical performance of many of the OECD and Latin American economies." According to Young's paper, the "Asian Tigers" do not have especially high growth rates of productivity, they are growing fast only because they are increasing the use of inputs tremendously. Paul Krugman (1994) echoed this opinion in his essay "The Myth of Asia's Miracle," stating that almost all East Asian output growth has been matched by rapid input growth.

Aggregate productivity refers to output per unit of input. It reflects technical change as well as technical efficiency change. In the study of economic growth, accounting for productivity growth is very important as the economy's long run growth is driven by productivity growth and to a lesser extent by growth in inputs. Young believes that growth in East Asia is driven by a scale effect, and that technical innovations are adopted no faster than in other countries.

In his 1995 paper, Young used a translog production function to represent the economy's aggregate technology, and estimated the "Solow residuals" to obtain TFP indexes for four different countries. In this model, technical efficiency in production is assumed, i.e., the economy is assumed to be producing on the frontier. He investigated the cases of Hong Kong, Singapore, Taiwan, and South Korea.

Despite spectacular economic performance in the last two decades in China, there are relatively few studies on China's overall productivity performance. Ezaki and Sun (1999) studied TFP growth for China. They reported that the growth rate of TFP has been fairly high, at about 3% to 4% from 1981 to 1995. They used a growth accounting approach directly from the data; no econometric estimation was done. In

his recent paper about China, Young (1999) estimated non-agricultural TFP growth rate to be 1.4% per year during the period of 1978 to 1998. Similar to his claim for the four "Asian Tigers", he stated "the productivity performance of the non-agricultural economy (of China) during the reform period is respectable, but not outstanding." Kalirajan et al (1996) studied agricultural total factor productivity (TFP) growth of the Chinese provinces, and reported that TFP growth in the pre-reform period of 1970-1978 was negative in twenty out of twenty-eight provinces. In the 1979-1983 reform period agricultural TFP growth was positive in almost all provinces, but it reverted to negative in sixteen out of twenty-eight provinces in the post-reform period of 1984-1987. Woo (1996) reported China's net TFP growth rate to be 1.1 to 1.3 percent from 1978 to 1993, and 0.3 to 0.6 percent from 1985 to 1993. Wu (1999) used a stochastic frontier approach to estimate TFP growth, including both the technical change rate and the efficiency change rate for Chinese provinces from 1978 to 1995. The TFP growth rates in this study have been increasing from a negative territory to positive, although still a small figure, during the reform period.

Traditionally, total factor productivity, the ratio of an index of aggregate output to an index of aggregate input, has been used to measure productivity. Changes in TFP can be decomposed into components measuring changes in technical efficiency, in scale, and in technology.

The purpose of this study is to obtain TFP growth rates at the provincial level for China for the reform period from 1978 to 1998. In order to understand more thoroughly the sources of economic growth, we isolate technological change from scale effects. This study differs from the above studies in five ways. First, we use panel data of real GDP, real capital stock, and labor force of all 30 provinces for 21 years. Second, instead of using traditional growth accounting by obtaining the shares of capital and labor from national accounts, we use a fixed-effect model and a stochastic frontier approach to estimate the contributions of capital and labor, and to obtain the TFP growth rate. We are also able to isolate efficiency change from technical change by province and year. Third, we try to explain the cross-province developmental difference by evaluating contributions from labor and capital for each province each year. Fourth, this approach emphasizes the use of quantities instead of prices because prices do not reflect opportunity cost in non-market economies. Fifth, a byproduct of the approach we use to estimate TFP growth is the specification of an aggregate production technology. We are able to estimate parameters such as output elasticities,

elasticities of substitution, elasticities of scale, and factor biases of technological change that more specifically describe the Chinese production sector.

We discuss the alternative methodologies for productivity analysis in section 2. In section 3, we report the results of the two different methods we used. We draw our conclusions in section 4.

2 Methodologies

Following the work of Solow (1957) and Griliches (1994), we break down the growth rate of aggregate output into contributions from the growth of inputs (capital and labor), and technological change. Let's start with a standard neoclassical production function.

$$Y(t) = A(t) \cdot F(K(t), L(t)) \quad (1)$$

Where $Y(t)$ stands for output in period t , $K(t)$ is capital and $L(t)$ is labor, and F is the aggregate function. $A(t)$ indexes the technology. Assuming technical change is Hicks neutral, the rate of growth of output is:

$$\dot{Y}/Y = \dot{A}/A + \frac{AF_K}{Y} \cdot \dot{K} + \frac{AF_L}{Y} \cdot \dot{L} \quad (2)$$

where F_K and F_L are the marginal products of capital and labor respectively, and a dot represents the time derivative of the variable. After a little manipulation, we have:

$$\dot{Y}/Y = \dot{A}/A + \frac{AF_K K}{Y} \cdot (\dot{K}/K) + \frac{AF_L L}{Y} \cdot (\dot{L}/L) \quad (3)$$

If we assume a competitive market, then the marginal product is equal to the ratio of input price to output price. If in addition we assume constant returns to scale, $\frac{AF_K K}{Y}$ is the share of the rental payments to capital, and $\frac{AF_L L}{Y}$ is the share of wage payments to labor ¹. Let $\frac{AF_K K}{Y} = \alpha(t)$ and $\frac{AF_L L}{Y} = \beta(t)$, then equation (3) can be written as

$$\dot{Y}/Y = \dot{A}/A + \alpha(t) \cdot (\dot{K}/K) + \beta(t) \cdot (\dot{L}/L) \quad (4)$$

¹Some of the papers mentioned above assume the existence of a competitive market, or a well-functioning market economy in their work on Chinese productivity measurement. Then the rental payments to capital and the wage payments to labor can be obtained from the national account. However, we believe this is not appropriate for the Chinese economy, since it is an economy in transition, far from a mature market economy. We estimate the contribution of capital and labor econometrically and avoid this assumption.

Thornquist (1936) has shown that the TFP growth rate between two points in time t and $t + 1$ in discrete time can be expressed as:

$$\log[A(t+1)/A(t)] = \log[Y(t+1)/Y(t)] - \bar{\alpha}(t) \cdot \log[K(t+1)/K(t)] - \bar{\beta}(t) \cdot \log[L(t+1)/L(t)] \quad (5)$$

Here $\bar{\alpha}(t) = [\alpha(t+1) + \alpha(t)]/2$ and $\bar{\beta}(t) = [\beta(t+1) + \beta(t)]/2$ are the average shares of capital and average share of labor over periods t and $t+1$. Diewert (1976) has shown that the index above is superlative and it is exact for a translog production function. We proceed then to measure TFP growth for China's provinces by econometrically estimating an aggregate translog production function. To account for the panel nature of the data two methods are used:

1. a translog production function with fixed effects,
2. a stochastic frontier translog production function.

In both cases the production technology is represented by

$$\begin{aligned} \log Y = & \alpha_0 + \alpha_K \log K + \alpha_L \log L + \alpha_t t + \frac{1}{2} \beta_{KK} (\log K)^2 + \\ & \beta_{KL} (\log K)(\log L) + \beta_{Kt} (\log K)t + \frac{1}{2} \beta_{LL} (\log L)^2 + \\ & \beta_{Lt} (\log L)t + \frac{1}{2} \beta_{tt} t^2 \end{aligned} \quad (6)$$

where Y , K , L and t , represent output, capital, labor and time (as a proxy for technical change), and α 's and β 's are parameters to be estimated. When fixed effects are used, dummy variables capturing the differences across the 30 provinces are included. When the stochastic frontier approach is used, the stochastic error is decomposed into an efficiency term and a term of measurement error or other random error. We follow Aigner, Lovell and Schmidt (1977) and Meeusen and van den Boeck (1977) who proposed the following stochastic frontier production function:

$$\log(y_i) = x_i \beta + v_i - u_i, i = 1, 2, \dots, N. \quad (7)$$

Here $\log(y_i)$ is the logarithm of the output for the i th firm or production unit. x_i is a vector, representing the right hand side of equation (6), whose first element is "1" and the remaining elements are the logarithm of all the input quantities. The error term, v_i , accounts for measurement error and other random factors, and is assumed to be independent and identically distributed (*i.i.d.*) as a normal distribution with

mean zero and constant variance, σ_v^2 . And u_i , a one-sided error term used to capture departure of the cross section units from those on the frontier, is assumed to be an *i.i.d.* half-normal or truncated normal variable. Here for generality, we assume u_i is a variable with truncated normal distribution.

Pitt and Lee (1981) specified a panel-data version of the Aigner, Lovell and Schmidt (1977) model:

$$\log(y_{it}) = x_{it}\beta + v_{it} - u_{it}, i = 1, 2, \dots, N; t = 1, 2, \dots, T. \quad (8)$$

This model is used in this study to estimate equation (6) for 30 Chinese provinces during the 21 years. It allows decomposition of TFP growth into efficiency change and technical change. An estimate of u_{it} provides a notion of the performance of each unit compared to the rest in each time period, for a stable technology. This is referred to in the literature as technical efficiency.

Total Factor Productivity growth is obtained in the fixed effects model as:

$$TFP_t^f = \frac{\partial \log Y}{\partial t} = \alpha_t + \beta_{Kt} \log K + \beta_{Lt} \log L + \beta_{tt} t \quad (9)$$

while in the stochastic frontier model, equation (9) only measures technical change (TC). TFP rates in the stochastic frontier model has two components: TC and EC (Efficiency Change):

$$TFP_t^s = TC_t + EC_t \quad (10)$$

Input contributions to output growth, the production elasticities, are

$$s_K = \frac{\partial \log Y}{\partial \log K} = \alpha_K + \beta_{KK} \log K + \beta_{KL} \log L + \beta_{Kt} t \quad (11)$$

$$s_L = \frac{\partial \log Y}{\partial \log L} = \alpha_L + \beta_{KL} \log K + \beta_{LL} \log L + \beta_{Lt} t \quad (12)$$

The above equations indicate the percentage change in output due to a 1% change in inputs. These elasticities give us a sense of the importance of input growth versus productivity growth in the explanation of output growth. They are also used to obtain an estimate of aggregate returns to scale. The elasticity of scale is defined as:

$$\epsilon = \frac{\partial \log f(\lambda x)}{\partial \log \lambda} |_{\lambda=1} = \sum_{i=1}^n \frac{\partial f}{\partial y} = \sum_i \epsilon_i \quad (13)$$

and measures how output varies as a particular input bundle is augmented by a scalar. For computational purpose, it can be rewritten as:

$$\epsilon = s_K + s_L \quad (14)$$

If the scale elasticity is unity, then the technology exhibits constant returns to scale. A scale elasticity greater than unity indicates increasing returns to scale and one below one indicates decreasing returns.

Two additional technology parameters are of interest, the substitution elasticity and the pairwise input bias. The substitution elasticity indicates the ease of factor substitution and is defined by Hicks as

$$\sigma_{KL} = \frac{\partial \log \frac{K}{L}}{\partial \log MRS_{KL}} \quad (15)$$

where MRS_{KL} refers to the marginal rate of technical substitution.

Hicks defined pairwise input bias due to technical change as

$$\beta_{KL} = \frac{\partial MRS_{KL}}{\partial t} = \frac{\partial MP_K}{\partial t} - \frac{\partial MP_L}{\partial t} \quad (16)$$

where MP_i stands for the marginal productivity of the i th input. It measures the rotation of the isoquant at a given point in input space in response to technological change. A zero value of indicates Hicks neutrality while a positive value indicates a labor augmenting technical change (or capital saving.)

3 Estimation and Results

The two approaches presented above are used to estimate productivity growth of the Chinese provinces. The dataset is composed of real GDP, real capital stock (both in million yuan of 1950) and labor force (in thousand workers) for all the 30 provinces of China from 1978 to 1998². Data on GDP, investment in Fixed Capital, and the labor force are obtained from *Comprehensive Statistical Data and Materials on 50 Years of New China*, and various issues of *China Statistical Yearbook*.

²GDP and investment have been deflated by the national general retail price indexes, with 1950 as the base year.

Because data on capital stocks for Chinese provinces is unavailable, we estimate the capital stocks from data on investment. To estimate capital stocks of the 30 provinces, we use the perpetual inventory method. The following formula is used:

$$K_t = (1 - \delta)K_{t-1} + I_{t-1} \quad (17)$$

where K_t represents the capital stock at time t , δ represents the depreciation rate, and I_{t-1} is the investment at time $t - 1$. The series of investment in fixed capital from year 1950 through 1998 is used to estimate the capital stock. Solving equation (15) gives,

$$K_{t+N} = (1 - \delta)^N K_t + \sum_{j=0}^{N-1} I_{t+j} (1 - \delta)^{N-j-1} \quad (18)$$

The depreciation rate is taken to be 0.0422, the average depreciation rate of fixed assets of state-owned enterprises from 1952 to 1992 (*Statistical Yearbook of China*, 1997). We are interested in obtaining the series of capital stock from 1978 to 1998. We have series of investment from 1952 to 1998. Suppose we use the capital stock at year 1952 as the benchmark capital stock K_t , then as years go by, $(1 - \delta)^N$ decreases, and the value of the benchmark capital stock becomes less important. We tested the sensitivity of the values of capital stocks with different values of the benchmark capital stock, and the final estimations of capital stocks of 1978 or later turned out to be almost identical. Capital stocks for all the 30 provinces have been estimated by equation (18).

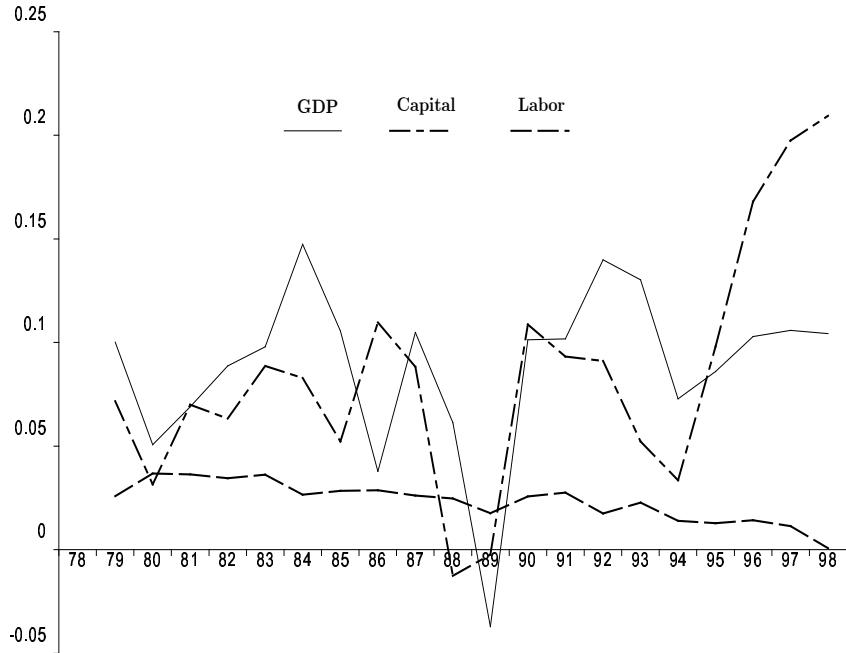
To study regional economic performance, the 30 provinces are grouped into three regions: East (mostly coastal provinces, 12 provinces), Central (9 provinces), and West (9 provinces)³. From 1978 to 1998, real GDP growth rates of the 30 provinces are shown in Table 1.

Table 1: Average Growth Rates of GDP, capital and labor, 1978 to 1998

Growth Rates	GDP	Capital	Labor
East	9.68%	10.61%	2.10%
Central	8.71%	7.69%	2.49%
West	7.91%	6.43%	2.53%
National	8.86%	8.49%	2.34%

³This is the traditional division of Chinese provinces, both economically and geographically.

Figure 1: Average Growth Rates of GDP, Capital and Labor, 1978-1998



We can see from Table 1 that most provinces experienced tremendous real GDP growth over the 21-year period, with a national average growth rate of 8.86%. Generally, the provinces in the East performed best, whereas provinces in the West had the poorest performance. It is interesting to note in Figure 1 that the average growth rate of GDP for the whole country was negative in the 1988-1989 period but this growth rate turned large and positive in subsequent periods. Is China's strong economic growth due to technological innovation, scale effects or just input growth? The answer to this question is important given that long run sustainability of such growth along with permanent improvements in the standard of living of the Chinese population depends crucially on its origins.

3.1 Productivity growth with fixed-effects models

After the addition of a stochastic error, the following translog production function is estimated using generalized least squares⁴ with a correction for heteroskedasticity:

$$\begin{aligned} \log Y = & \alpha_0 + \sum_{i=1}^{29} \alpha_i D_i + \alpha_K \log K + \alpha_L \log L + \alpha_t t + \frac{1}{2} B_{KK} (\log K)^2 + \\ & B_{KL} (\log K) (\log L) + B_{Kt} \log K \cdot t + \frac{1}{2} B_{LL} (\log L)^2 + \\ & B_{Lt} \log L \cdot t + \frac{1}{2} B_{tt} t^2 + \xi \end{aligned} \quad (19)$$

where Y stands for real GDP and K , L , and t denote capital input, labor input, and time. Dummy variables were included in the estimation to capture heterogeneity of the fixed effects variety across provinces not captured by the inputs.

Two nested models are tested. If all second order coefficients are zero, then the translog becomes a Cobb Douglas. This restriction is tested using a Wald test and rejected by the data⁵. This is important given the prevalence of the Cobb-Douglas form in aggregate studies of growth. Another important restriction used in the indexing approaches to productivity growth and in some econometric studies is that of constant returns to scale (CRS). Under this assumption, the following restrictions must be satisfied:

$$\alpha_K + \alpha_L = 1, \quad B_{KK} + B_{KL} = B_{LL} + B_{KL} = B_{Kt} + B_{Lt} = 0. \quad (20)$$

The hypothesis of CRS is tested with a Wald test and rejected by the data⁶. We proceed to estimate a translog production function without the CRS restriction. Symmetry of cross effects is maintained throughout the estimation. A total of 630 observations are used in the estimation of 39 parameters. Of these parameters, 29 are dummy variables, 9 are the first and second order parameters of the production function and one is the constant. Among the nine production function parameters, three of them are significant at the 99% level, one is significant at 95% level, and one is at 90% level (See Appendix 1).

⁴The Eviews econometric package is used in this estimation.

⁵Results of Wald test for Cobb-Douglas form: $\chi^2 = 196.2883$, $p - value = 0.0000$.

⁶Results of Wald test for CRS: $\chi^2 = 123.5373$, $p - value = 0.0000$.

Our main interests are the estimations of the rate of technical change, the scale elasticity and the contribution of inputs to output growth. To estimate the rate of technical change we use equation (9) with parameters estimated by this model

$$TFP_t^f = \frac{\partial \log Y}{\partial t} = \hat{\alpha}_t + \hat{B}_{Kt} \log K(t) + \hat{B}_{Lt} \log L(t) + \hat{B}_{tt} t \quad (21)$$

where hats represent estimated parameters. Equation (21) is evaluated at each data point and an average across time and for each region is presented in Table 2 (See Appendix 1 for more detailed results).

Table 2: Growth Patterns of the Three Regions of China (Translog Production Function with Fixed-effect Model): Averages from 1978 to 1998

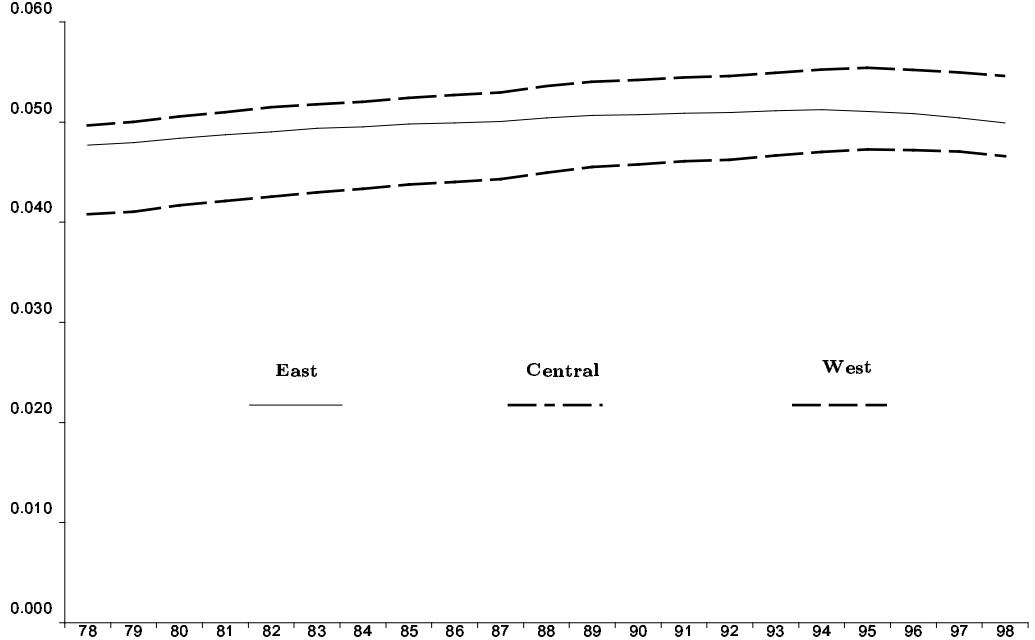
	TFP Growth Rates	s_k	s_l	Contri. of K	Contri. of L	Contri. of TFP	Elasti. of Substi.	Tech. Biases
East	0.050	0.365	0.333	0.437	0.098	0.582	0.242	0.086
Central	0.053	0.382	0.252	0.373	0.091	0.487	0.155	0.053
West	0.045	0.334	0.491	0.304	-0.082	0.114	0.509	0.054
National	0.049	0.361	0.356	0.378	0.042	0.413	0.296	0.067

Note: s_k and s_l represent output elasticity of capital and labor, respectively.

Table 2 indicates that the estimated average productivity growth in China during this twenty-year period is approximately 4.9% annually. This rate is much higher than that estimated in other studies for OECD countries (about 2%) and it explains approximately 41 percent of the average GDP growth of 8.86%. Productivity growth explains approximately 58 percent of GDP growth in the fast growing provinces of the East. It explains approximately 49 percent of GDP growth in the Central provinces. However, it only explains about 11 percent in the slower growing West provinces. This indicates that the process of adopting technological innovation in the backward western provinces is much slower than other parts of the country. The parameter β_{tt} indicates that productivity is increasing at an increasing rate of 0.0094% annually, for the country as a whole.

The contribution of capital and labor to output, the production elasticities, are calculated using equations (11) and (12) which in terms of the estimated parameters are

Figure 2: Average TFP Growth Rates



$$\hat{s}_K(t) = \hat{\alpha}_K + \hat{B}_{KK} \log K(t) + \hat{B}_{KL} \log L(t) + \hat{B}_{Kt} t \quad (22)$$

$$\hat{s}_L(t) = \hat{\alpha}_L + \hat{B}_{KL} \log K(t) + \hat{B}_{LL} \log L(t) + \hat{B}_{Lt} t \quad (23)$$

These elasticities are evaluated at each data point. Table 2 presents summaries of the capital and labor production elasticities for the three regions. From this table we see that in the East, labor changes have slightly smaller impact than capital changes on output growth. In the Central region (the traditionally labor abundant region), capital has the biggest impact on output growth while labor changes have the smallest impact among three regions. On the other hand, in the West region (labor scarce region), labor changes have the biggest impact among three regions while capital changes have the smallest impact. On average, a 1% increase in capital induces a 0.361% increase in GDP while a 1% increase in labor accounts for a 0.356% output increase.

In order to account for the actual contribution of inputs to output growth, we use these estimated elasticities along with the actual growth in the two factors

for all provinces and all years to calculate the contributions from labor and capital. These results are summarized in Table 2, which indicates that capital and labor have accounted for 37.8% and 4.2%, respectively, of average GDP growth, and TFP growth has accounted for 41.3% of the GDP growth in China during the reform period. Capital contributes 43.7% of the GDP growth in the East region, while 37.3% and 30.4% in the Central and West, respectively. This result shows that the fast growth of the East region of China is considerably due to rapid increase of capital investment, such as foreign direct investment in Guangdong province. However, at the same time, we should also notice that TFP contribution for the GDP growth is even bigger for the East region. The contribution of labor growth is unsurprisingly low, given that labor supply is almost unlimited and the growth rate of labor is small due to the birth control policy adopted by the Chinese government. Among the three regions, the East has the highest contribution from TFP growth, 58.2%. That shows that during the reform period, contrary to Young's conclusions, at least the East region in China has benefited substantially from technology innovation relative to factor accumulation.

Three conclusions result from the estimates presented above. First, input growth and technological change have similar contributions to overall GDP growth (42% versus 41.3%). Second, capital growth has contributed more than labor. Third, output growth is less than accounted for by input growth and productivity growth, indicating the presence of other than constant returns to scale⁷.

This takes us to the next concept of importance in this study, the scale elasticity, calculated here by equation (12). This elasticity indicates that the aggregate Chinese technology shows decreasing returns to scale, or that an increase in inputs of the same magnitude increases output less than proportionally. Therefore, the contribution of inputs to output growth reflects this characteristic of the technology.

An important parameter describing the nature of the input substitution possibilities in this economy is the elasticity of substitution. This elasticity is obtained evaluating equation (15) with the estimated parameters and at each data point. Table 2 summarizes this information and indicates a high degree of substitution between capital and labor in the West region. This indicates that in the backward western provinces, labor and capital are highly substitutable, compared to other provinces.

The nature of technical change that occurred in the Chinese economy can be explored further by the calculation of input biases. In doing so, we use Hicks' def-

⁷Remember that the data has rejected the CRS restriction.

inition of pairwise biases. Equation (16) is evaluated at each data point using the estimated parameters and the results are summarized in Table 2. This table indicates that technical change has been biased in favor of capital.

3.2 Productivity growth with a translog stochastic production frontier

Following Battese and Coelli (1993), we use a translog production function incorporating a model for technical efficiency effects. The equation to estimate is

$$\begin{aligned} \log Y_{it} = & \alpha_0 + \alpha_K \log K_{it} + \alpha_L \log L_{it} + \alpha_t t + \frac{1}{2} B_{KK} (\log K_{it})^2 + \\ & B_{KL} (\log K_{it})(\log L_{it}) + B_{Kt} \log K_{it} \cdot t + \frac{1}{2} B_{LL} (\log L_{it})^2 + \\ & B_{Lt} \log L_{it} \cdot t + \frac{1}{2} B_{tt} t^2 + v_{it} - u_{it} \end{aligned} \quad (24)$$

where v_{it} is a random error and u_{it} is a one-sided error term described in section 2. And they are assumed to be independently distributed: v_{it} 's are i.i.d. $N(0, \sigma_v^2)$ and u_{it} 's are $N(\mu_{it}, \sigma_u^2)$. The cross-region performance differences (i.e., the inefficiency effects) are hypothesized to be influenced by the degree of industrialization, openness, and infrastructure of each province. We believe in the case of Chinese economy, these three aspects are important for determining the production efficiency of each province. We specify the inter-provincial differences as:

$$u_{it} = \delta_0 + \delta_1(Ag_{it}) + \delta_2(Trade_{it}) + \delta_3(Rail_{it}) + w_{it} \quad (25)$$

where Ag_{it} is the ratio of total output in agriculture and GDP for each province at time t .

$Trade_{it}$ is the sum of import and export divided by GDP for each province at time t .

$Rail_{it}$ is the length of railway divided by the area of each provinces at time t .

w_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2 .

The ratio of agricultural output and GDP is a measure of degree of industrialization. Total volume of import and export divided by GDP is a measure of openness.

The condition of infrastructure of each province is proxied by the length of railway divided by the total area of each province.

Productivity growth can be decomposed into a component due to technological innovations and a component due to intrinsic differences across provinces. Technical change is captured by equation (9) while cross-province differences or what we refer to as efficiency change is given by estimates of the one-sided error term which indicate the distance of the cross sectional units from those on the frontier. The technical efficiency indicators give a sense of the cross-section heterogeneity among the provinces. The parameters of equations (24) and (25) are estimated using Coelli's FRONTIER 4.1 econometric package. This provides maximum likelihood estimates of the parameters of interest. Estimation results are reported in Table 2A in the appendix. From Table 2A we can see that δ_1 is estimated to be significantly negative, meaning agricultural provinces tend to be more inefficient in production; and δ_2 is estimated to be significantly positive, meaning openness has a positive effect on technical efficiency.

The restrictions for a Cobb-Douglas version are imposed and a likelihood ratio test indicates rejection of such a form. Also, a likelihood ratio test indicates rejection of the restrictions for constant returns to scale in production. Both of these results are consistent with our previous estimation. We proceed to estimate an unrestricted translog production frontier with symmetry maintained. Fourteen parameters are estimated, the ten production function parameters plus four parameters related to the error terms. Seven parameters are significantly different from zero at the 99% confidence level. Estimation results are presented in the appendix.

A summary of the estimated rates of technical change for each region and all years is presented in Table 3.

The stochastic frontier approach can separate the effects of technical change and efficiency change. In Table 3, we report technical change rates for the three regions and for the whole nation. Table 4 and Table 2H in the appendix report efficiency change rates for the three regions and for the whole nation. Technical efficiency change rates are positive for most provinces in most years.

In Table 3, we see that the average technical change rate for the whole nation is 2.7%, whereas national average TFP growth rate estimated by the fixed-effects model is 4.9% (reported in Table 2). There are two reasons for this difference. First, the contribution of capital with the stochastic frontier model is significantly higher than with the fixed effect model. Therefore, the stochastic frontier model gives smaller

Table 3: Growth Patterns of the Three Regions of China (Translog Production with Stochastic Frontier Method): Averages from 1978 to 1998

	Tech. Change Rates	s_k	s_l	Contri. of K	Contri. of L	Contri. of TC	Elasti. of Substi.	Tech. Change Biases
East	0.027	0.557	0.502	0.729	0.152	0.291	0.304	0.038
Central	0.029	0.486	0.486	0.510	0.177	0.281	0.281	0.039
West	0.026	0.424	0.612	0.418	-0.016	0.055	0.298	0.036
National	0.027	0.496	0.530	0.570	0.109	0.217	0.295	0.038

Note: TC represents Technical Change.

estimates for the contribution of technical change. Second, technical efficiency rates are positive. Therefore, part of the TFP growth rate from the fixed-effects model is actually technical efficiency change. We proceed to compare TFP growth in both models.

As we have seen in section 3.1, the East region does not have the highest TC growth rates; instead, it only has the same average growth rate of TC as the country as a whole, 2.7%. On the contrary, the contribution from capital investment is the highest in the East region: 72.9%. This, again as in section 3.1, is consistent with the conclusion of Young, among others, that China's rapid growth is largely due to rapid growth of investment only, technological improvement is nothing remarkable. However, we should note that this is only true for the East region; for the other two regions, capital investment contributes significantly for GDP growth but not as dominant. TC growth also plays an important role in the East and Central regions, with contributions to GDP growth 29.1% and 28.1% respectively. As we have seen in section 3.1, the West region benefited little from TFP growth. According to stochastic frontier method estimates, TC growth for the West region contributes only about 5.5% to its GDP growth rate, confirming our conclusion in section 3.1 that the West has not shown impressive technological improvements during the reform period.

Production elasticities of capital and labor calculated according to equations (11) and (12), evaluated at each data point and averaged for each region are reported in Table 3.

Again, the stochastic frontier model shows us a similar pattern as our estimation results with fixed-effect model. The capital production elasticity is 0.496 on average

and the East region has the highest capital production elasticity of 0.557 while the West region has the lowest capital production elasticity of 0.424. This elasticity has been increasing through time. The average labor production elasticity for the whole country is estimated to be 0.530. The West region has the highest labor production elasticity of 0.612, while the Central region (labor abundant region) has the lowest labor production productivity of 0.486.

Growth decomposition, from Table 3, indicates that on average capital growth and labor growth account for 57.0% and 10.9% of the growth rate of GDP respectively. The total contribution by factors, 67.9%, indicates that factor accumulation has been indeed the major factor that keeps the Chinese economy growing at a high speed. TC contributes only 21.7% of the GDP growth according to these estimates.

Again, three conclusions are possible from these results. First, input growth has contributed a major percentage of the overall GDP growth. Second, capital growth alone contributes more than 50% of the GDP growth, while labor growth and TC growth each accounts for less than 20%. This stresses the importance of capital investment in China, especially foreign investment. Third, average TC rate is low, however still higher than Young's estimation.

The scale elasticity calculated using equation (12) also indicates increasing returns in production for the East and West regions, and decreasing returns for the Central region. Substitution elasticities in Table 3 indicate a relatively low degree of substitutability between capital and labor in production.

In addition, technical efficiency, the amount of output per unit of input obtained by each province relative to other provinces when the technology is stable (no shifts through time due to technical change) is estimated by this method. Results presented in Table 4 and Figure 3 indicate that overall technical efficiency of the Chinese economy is about 73.3% and has had an increasing trend during the reform period. A more detailed report of technical efficiency estimations is listed in the appendix. It is interesting here to note the performance of the different regions. The East region shows the best performance, with an average efficiency of 82.1%, with most of the provinces closer to the upper bound of the frontier. The Central region shows an average efficiency of 70.4% at the highest rate increasing through time and the West provinces show the worst performance with an average efficiency of 64.3% also increasing through time. It is interesting to note that Shanghai has the highest average efficiency over the reform period, 95.7%, with Guangdong at the second place, 91.9%. On the other

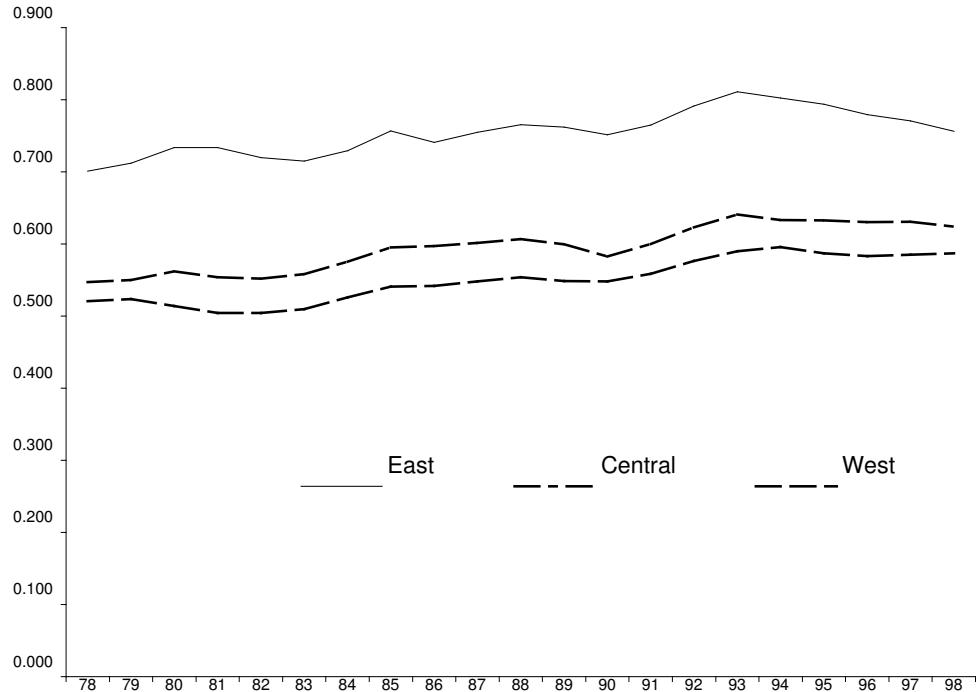
hand, Guizhou has the worst efficiency record of 48.1%, with Tibet at the second place, 51.2%. It indicates that Shanghai has almost always been on the frontier of the production possibility frontier, while Guizhou and Tibet have been deeply inside the production possibility frontier. From Table 4 and Figure 3 we can see that the average technical efficiency has been increasing over the reform period at a small rate of 0.6% per year.

Table 4: Average Efficiency of the Three Regions of China: Averages from 1978 to 1998

	Efficiency	EC Rate
East	0.821	0.005
Central	0.704	0.007
West	0.643	0.006
National	0.733	0.006

Note: EC represents Efficiency Change.

Figure 3: Technical Efficiency



After calculating technical efficiency change rates (see Appendix 2 for details), we are able to combine technical change rates and efficiency change rates to estimate TFP growth rates by equation (10). Table 5 summarizes TFP growth rates and its contribution to GDP growth estimated by both fixed-effects model and stochastic frontier model.

Table 5: Average TFP growth rates and TFP contributions by two models.

	TFP^f	C_{TFP}^f	TFP^s	C_{TFP}^s
East	0.050	0.582	0.031	0.486
Central	0.053	0.487	0.035	0.230
West	0.045	0.114	0.032	0.413
National	0.049	0.413	0.033	0.387

In table 5, TFP^f and C_{TFP}^f represent TFP growth rates and contribution to GDP growth by fixed-effects model. TFP^s and C_{TFP}^s represent TFP growth rates and contribution to GDP growth by stochastic frontier model.

From Table 5, we can see that after combining the technical change rates and efficiency change rates, we obtain TFP growth rates more comparable with the results from fixed-effects model. Both models estimated TFP growth rates in the period of 1978 to 1998 to be significantly higher than the estimates from Young (2000). Furthermore, the contribution of TFP to GDP growth is estimated to be 38.7% as a national average, which is also comparable to the result from the fixed-effects model. As we mentioned before, since fixed-effects model assumes full efficiency, we do not expect the two models return same results.

4 Conclusions

Regional estimates consistently indicate better productivity performance by the central provinces, medium by the east provinces and poor performance by the west provinces. In terms of efficiency estimations, the East region is more efficient than the others but its rate of improvement is lowest than that of the other regions. This indicates that the other regions are "catching up." It is interesting to note the performance of Shanghai and Guangdong at one extreme, and Tibet and Guizhou on the other.

Technical change's contribution to GDP growth is estimated as 21.7% by the stochastic frontier model, with rates of growth of technical change of approximately

2.7% for the whole country, a little lower in the West region and a little higher in the Central region.

The most important estimate though is that of total factor productivity growth. This study estimates a rate of productivity growth of 4.9% in the fixed effects model and 3.3% in the stochastic frontier model. Both models identify the Central region as the one with the highest average rate of productivity growth. TFP's contribution to GDP growth is 41.3% in the fixed effects model and 38.7% in the stochastic frontier model. Both models show an important contribution of improved efficiency and innovations on output growth in the Chinese economy.

Although TFP has contributed considerably to GDP growth, labor and capital growth still accounts for the majority of GDP growth. This indicates an important role for input growth and scale. In fact, the econometric estimates indicate capital growth dominating labor growth in accounting for output growth. Technological change has been labor using relative to capital, an indication in support of the induced innovation hypothesis given the very elastic supply of labor in China.

In conclusion, even though China's input growth accounts for a dominant percentage of the GDP growth, China still showed a rapid growth of productivity, which is still higher than that of the OECD economies and higher than Young (1995 and 2000) has estimated for China as well as other eastern Asian countries.

5 Appendix

APPENDIX 1: Estimation Results by Fixed-Effect Model (Table 1A-1H)

APPENDIX 2: Estimation Results by Stochastic Frontier Model (Table 2A-2I)

Table 1A. Estimation Results of Equation (17) by Fixed-Effect Model

Parameter	Estimates	T-ratios
α_0	-13.6513	-5.7515
α_K	-0.6521	-3.6417
α_L	3.9614	7.2674
α_t	0.0023	0.0993
B_{KK}	-0.0382	-2.3777
B_{KL}	0.1136	4.0327
B_{Kt}	0.0105	3.0845
B_{LL}	-0.2259	-6.9756
B_{Lt}	0.0015	0.4402
B_{tt}	-0.0003	-1.3306
$\alpha_0 + \alpha_1$	-13.8633	-5.8637
$\alpha_0 + \alpha_2$	-13.5531	-5.7374
$\alpha_0 + \alpha_3$	-14.1061	-5.9127
$\alpha_0 + \alpha_4$	-14.2577	-5.9770
$\alpha_0 + \alpha_5$	-13.3828	-5.6254
$\alpha_0 + \alpha_6$	-14.0338	-5.8816
$\alpha_0 + \alpha_7$	-13.6180	-5.7109
$\alpha_0 + \alpha_8$	-13.2433	-5.5622
$\alpha_0 + \alpha_9$	-13.1461	-5.5907
$\alpha_0 + \alpha_{10}$	-13.5000	-5.6964
$\alpha_0 + \alpha_{11}$	-13.7460	-5.8117
$\alpha_0 + \alpha_{12}$	-13.9153	-5.8312
$\alpha_0 + \alpha_{13}$	-14.0066	-5.8829
$\alpha_0 + \alpha_{14}$	-13.1804	-5.6294
$\alpha_0 + \alpha_{15}$	-13.5327	-5.7745
$\alpha_0 + \alpha_{16}$	-13.5882	-5.7335
$\alpha_0 + \alpha_{17}$	-13.5826	-5.7584
$\alpha_0 + \alpha_{18}$	-13.1837	-5.5902
$\alpha_0 + \alpha_{19}$	-14.0893	-5.9285
$\alpha_0 + \alpha_{20}$	-14.6110	-6.2474
$\alpha_0 + \alpha_{21}$	-13.4825	-5.7619
$\alpha_0 + \alpha_{22}$	-14.5443	-6.1012
$\alpha_0 + \alpha_{23}$	-14.2108	-5.9723
$\alpha_0 + \alpha_{24}$	-14.9006	-6.6500
$\alpha_0 + \alpha_{25}$	-14.2408	-5.9741
$\alpha_0 + \alpha_{26}$	-14.5176	-6.0848
$\alpha_0 + \alpha_{27}$	-14.7308	-6.3866
$\alpha_0 + \alpha_{28}$	-14.7508	-6.3997
$\alpha_0 + \alpha_{29}$	-14.3147	-6.0236

Table 2A. Estimation Results by Stochastic Frontier Model

Parameter	Estimates	T-ratios
α_0	-0.4520	-4.4051
α_K	0.5159	2.1523
α_L	0.9695	3.1179
α_t	-0.0044	-0.1865
B_{KK}	0.1136	3.1361
B_{KL}	-0.1264	2.3319
B_{Kt}	-0.0037	-0.5874
B_{LL}	0.0097	0.3615
B_{Lt}	0.0059	1.2436
B_{tt}	-0.0002	-0.5135
δ_0	0.3309	6.9349
δ_1	-0.0482	-10.4518
δ_2	0.9233	6.3457
δ_3	0.000018	0.0932

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