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Rural Education, Technological Progress and Productivity Growth in China's Agriculture

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This paper examines the impacts of rural education on agricultural productivity in China. The approach we take involves two-stage process. First, we use DEA_Malmquist method to measure total factor productivity change, technical change and efficiency change in China over the period 1985 to 2011. We find that China has experienced an increase in total factor productivity, and that productivity growth was mostly attributed to technical progress, rather than to improvement in efficiency. And then, with a panel dataset covering 30 provinces, we investigate the impact of rural education on productivity growth of China. The results indicated that the development of rural education plays positive role on China's agricultural productivity growth. Moreover, empirical results of regression models show that rural education enhances agricultural total factor productivity through technological progress rather than by promoting technical efficiency.

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1. Introduction

China's rural education reform started in 1984, and experienced a milestone in 2006 when the Chinese government made primary school and the first three years of secondary school free for all children in rural area. The Chinese central government has invested 61.8 billion yuan ($10.1 billion) improving school houses and educational facilities in rural areas over the past four years[1]. In 2012, 4.2 percent of China's GDP was allocated to the education sector and 30 percent of that amount was spent on developing basic education in rural areas of poor provinces in central and western parts of the country[2]. However, China is seeing an increasingly large gap between the education levels of people holding urban and rural permanent residency permits. A survey showed that only 26.8% of the students in the countryside continued schooling after finishing junior high school, which is covered by China's nine-year compulsory education plan and qualifies for subsidies[3]. It was important to improve rural education as it is a matter concerning the long-term development of rural areas and the improvement of rural labor's skills. Public spending on research, extension and education leads to accumulations of modern technologies. Knowledge and human capital would be expected to raise productivity of all factors of production. Well-educated farmers would be better positioned to adopt advancing technologies. The development of vocational education for professional farmers will promote agricultural modernization. At the end of 2012, there were 12,663 secondary vocational schools in China, with 21.13 million students. About 2.19 million students were majoring in agriculture, forestry and fishing, accounting for only 10.35 percent of the total[4].

Endogenous growth theorists such as Romer (1986, 1990) and Lucas (1988, 1993) stated that research and development (R&D) and human capital are two of the most influential forces capable of boosting productivity. Accumulation of human capital can sustain long term growth. There is nearly no doubt better-educated man lead a better life, however, there are arguments against the role of education on agricultural productivity. Pritchett (1996) showed a counter-intuitive phenomenon education played negative role on total factor productivity, and he explained that although schooling has increased worker intellectual skills, but an ineffective institutional environment provides little opportunity for workers to use these skills in production. The purpose of this paper is to revisit this issue, using a panel provincial data from China.

This paper's contribution to the literature arises from it provides empirical evaluation on the role of rural education on agricultural total factor productivity. Agricultural technologies include all

1 http://www.chinadaily.com.cn/business/2014-02/14/content_17282518.htm
2 http://www.chinadaily.com.cn/opinion/2014-03/04/content_17319500.htm
3 http://www.chinaeconomicreview.com/china-eye/2009_03_10/rural-and-urban-education-levels-gap-massive.html.
4 http://news.xinhuanet.com/english/china/2013-07/22/c_132563705.htm.

kinds of improved techniques and practices which affect the growth of agricultural output, such as high-yielding varieties of seeds, chemical fertilizers, pesticides, use of machinery, etc. By controlling for potential factors such as the agricultural share of rural labor, industry structure, mechanical intensity and natural disasters, we examine the effects of rural education on agricultural total factor productivity, technical progress, and technical efficiency using China's provincial-level data from 1985 to 2011.

The remainder of the paper is organized as follows. The next section provides a literature review. The third section presents the methodological framework, and then data and empirical results are discussed in the fourth section. The last section draws conclusions.

2. LITERATURE REVIEW

Schultz (1975) suggested that education improves an individual's ability to allocate resources and response more quickly to the changing economic conditions or economic disequilibria. Empirical studies focused on the return to education of agricultural production found different evidence in different regions. Jamison and Lau (1982) summarized the results of over 35 studies from Asia, Africa, and Latin America that measure returns to the education of farmers. The estimated return to education is positive and significant at the 0.05 level in 17 of the 22 studies from Asia. Thirteen studies from Latin America cases reveals that education has no (or a negative) effect on productivity. Huffman (1974) found that the return to education from increasing allocative efficiency is three times larger than the return from the change in technical efficiency. Foster and Rosenzweig (1996) presented evidence that there is an important interaction between technological change and schooling for rural households. In Asia, Yang (1997) discovered there existed positive and significant direct effect of secondary education on agricultural productivity. Fafchamps and Quisumbing (1998) investigated whether human capital raises the productivity and labor allocation of rural households in four districts of Pakistan, and they found that education has no significant effect on productivity in crop and livestock production. Jolliffe (2004) found similar evidence that more educated people are allocated away from the farm, the negative effect of off-farm effects overriding the positive effect of education on agricultural productivity. Benin et al. (2009) estimated the agricultural productivity returns to different types of public expenditure using the data of Ghana, and revealed that formal education was negatively associated with agricultural productivity. The improvement of rural human capital promotes off-farm employment opportunities and exit options out of agriculture to the extent that it reduces the knowledge and skills of those left on the farm. Alene and Manyong (2007) suggested possible reasons for the lack of significance of education in the African studies, including the problem of consistency of the design of the studies and analytical methods. Kumar and Chen (2013) studied the impact of education and health on the growth rate of TFP in a sample of 97 countries for the period 1960-2005, and revealed that education have a positive and significant effect on the growth rate of TFP.

The above empirical evidences revealed by different scholars vary systematically by region, and these different empirical research conclusions illustrate the need for further investigation of the effects of rural education on agricultural productivity in China.

3. Methodological framework

3.1. Malmquist Productivity Index

The Malmquist productivity index (MPI) is first proposed by Caves, Christensen and Diewert (1982), which is an important measure of production pattern. The MPI can describe multi-input and multi-output production without involving cost data only with quantity data . The MPI has been widely used since Färe et al. (1994) applied the data envelopment analysis (DEA) approach to estimate and decompose the MPI. The DEA method is a non-parametric approach and does not require the prior specification of the form of production function and the distribution of the inefficiency term. In the current study, the output-oriented DEA model is used to measure the productivity change of China's agriculture. Following Shephard (1970) and Färe (1988), the output-oriented distance function for the period t can be defined as:

$$d_o^t(q_t, x_t) = \inf\left[\theta : (x_t, q_t/\theta) \in S^t\right] \tag{1}$$

Where x_t is the inputs vector at time period t, q_t is the outputs vector, the superscript t denotes the time period of reference technology, and S^t is the technology set with $S^t = \{(q_t, x_t) : x_t \textit{ can produce } q_t\}$. Consequently, based on different benchmark technology and time periods, four distance functions can be defined, i.e. $d_o^t(q_t, x_t)$, $d_o^s(q_s, x_s)$, $d_o^t(q_s, x_s)$, and $d_o^s(q_t, x_t)$. According to Färe et al. (1994), the output-oriented Malmquist TFP change index between period s (the base period) and period t is given by:

$$m_o(q_s, x_s, q_t, x_t) = \left[\frac{d_o^s(q_t, x_t)}{d_o^s(q_s, x_s)} \times \frac{d_o^t(q_t, x_t)}{d_o^t(q_s, x_s)}\right]^{1/2} \tag{2}$$

MPI is measured by the geometric mean of the two efficiency ratios: the one being the efficiency change measured by the period s technology, and the other the efficiency change measured by the period t technology. In order to calculate this productivity index, the above four distance functions can be calculated as solutions to the following four linear programming (LP) problems. Färe et al.

(1994) assumed a constant returns to scale (CRS) technology in their analysis. The required LPs are:

$$\begin{aligned}&[d_o^t(q_t, x_t)]^{-1} = \max_{\phi,\lambda} \phi,\\ &st. -\phi q_{it} + Q_t\lambda \geq 0,\\ &\quad \mathrm{x}_{it} - X_t\lambda \geq 0,\\ &\quad \lambda \geq 0,\end{aligned} \tag{3}$$

$$\begin{aligned}&[d_o^s(q_s, x_s)]^{-1} = \max_{\phi,\lambda} \phi,\\ &st. -\phi q_{is} + Q_s\lambda \geq 0,\\ &\quad \mathrm{x}_{is} - X_s\lambda \geq 0,\\ &\quad \lambda \geq 0,\end{aligned} \tag{4}$$

$$\begin{aligned}&[d_o^t(q_s, x_s)]^{-1} = \max_{\phi,\lambda} \phi,\\ &st. -\phi q_{is} + Q_t\lambda \geq 0,\\ &\quad \mathrm{x}_{is} - X_t\lambda \geq 0,\\ &\quad \lambda \geq 0,\end{aligned} \tag{5}$$

$$\begin{aligned}&[d_o^s(q_t, x_t)]^{-1} = \max_{\phi,\lambda} \phi,\\ &st. -\phi q_{it} + Q_s\lambda \geq 0,\\ &\quad \mathrm{x}_{it} - X_s\lambda \geq 0,\\ &\quad \lambda \geq 0,\end{aligned} \tag{6}$$

The MPI defined in equation (2) can be further decomposed into two components, i.e., efficiency change (Catch-up term) and technical change (Frontier-shift term). The catch-up (or recovery) term relates to the degree to which a DMU improves or worsens its efficiency, while the frontiers-shift (or innovation) reflects the change in the efficiency frontiers between the two time periods. [5]

$$m_o(q_s, x_s, q_t, x_t) = \frac{d_o^t(q_t, x_t)}{d_o^s(q_s, x_s)} \times \left[\frac{d_o^s(q_t, x_t)}{d_o^t(q_t, x_t)} \times \frac{d_o^s(q_s, x_s)}{d_o^t(q_s, x_s)}\right]^{1/2} \tag{7}$$

Where the ratio outside the square bracket measures the efficiency change between time period s and t, which captures the degree of catching up to the best-practice frontier. The remaining part is a measure of technical change, which captures the shift in the frontier between these two periods.

$$Efficiency\,change = \frac{d_o^t(q_t, x_t)}{d_o^s(q_s, x_s)} \tag{8}$$

Efficiency change (Cath-up) >1, indicates progress in relative efficiency from period s to period t, while efficiency change =1 or <1, indicates no change or regress in efficiency.

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[5]Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*. Springer Science & Business Media, p328.

$$Technical\ \ change = \left[\frac{d_o^s(q_t, x_t)}{d_o^t(q_t, x_t)} \times \frac{d_o^s(q_s, x_s)}{d_o^t(q_s, x_s)} \right]^{1/2} \quad (9)$$

Tchnical change >1 indicates progress in the frontier technology from period s to period t, while technical change=1 and technical change <1 indicate the status quo and regress in the frontier technology. MPI is the product of efficiency chang and technical change. MP>1 indicates progress in total factor productivity from period s to period t, while MP=1 and MP<1 respectively indicates the status quo and deterioration in the total factor productivity.

The output variable used in DEA analysis is the gross output value of farming, forestry, animal husbandry and fishery. Five inputs are specified: land, labor, machinery, fertilizer and irrigation. The detaileld definitions of output and input variables are explained in section 4.

3.2. Econometric Model

In order to investigate the impact of rural education on the growth rate of total factor productivity and its two components, i.e., the growth rate of technical efficiency and that of technical progress, are respectively used as the dependent variables. Among the explanatory variable, in addition to rural education, an indicator of human capital, a list of factors that are beyond the control of the producers themselves are also included.

As for control variables, the first one *(industry)* is the industry share of GDP, which relates to the economic structure. The second one *(rural_labor)* is the agriculture's share of the rural labor force. Yao and Liu (1998) forwarded that if the ratio of agriculatural labor to rural labor is large, there must be labor-surplus problem, and the efficiency of production is relative low. The third control variable *(machine_intensity)* is the ratio of mechnical power to agricultural labor. *Machine_intensity* is adopted to examine the impact of promoting eagicultural engineering progress on the productivity improvement. In order to control for the different geographic and natural production conditions, the fourth control varialbe *(affected)* the ratio of natural disaster affected area to cultivated area is also included. A trend vriable *(T)* is also in the list of regressors, which is a proxy of institutional and economic enviorment change.

The regression models can be described as follows:

$$\dot{TFP}_{it} = \alpha_0 + \alpha_1 education_{it} + \alpha_2 industry_{it} + \alpha_3 rural\_labor_{it} + \alpha_4 machine\_intensity_{it} + \alpha_5 affected_{it} + \alpha_6 T_t + \mu_i + \varepsilon_{it} \quad (10)$$

$$\dot{TP}_{it} = \gamma_0 + \gamma_1 education_{it} + \gamma_2 industry_{it} + \gamma_3 rural\_labor_{it} + \gamma_4 machine\_intensity_{it} + \gamma_5 affected_{it} + \gamma_6 T_t + \omega_i + \xi_{it} \quad (11)$$

$$\dot{TE}_{it} = \beta_0 + \beta_1 education_{it} + \beta_2 industry_{it} + \beta_3 rural\_labor_{it} + \beta_4 machine\_intensity_{it} + \beta_5 affected_{it} + \beta_6 T_t + \nu_i + \psi_{it} \quad (12)$$

Where $TFP_{it}, TE_{it}, TP_{it}$ are calculated from previous output-oriented CRS DEA_Malmquist model; μ_i, ν_i, ω_i are the unobservable province-level specific effect; $\varepsilon_{it}, \psi_{it}, \xi_{it}$ are the error terms. Table 1 presents the definition of variables.

<<Insert Table 1 here>>

Since the unit of observation in our study is a province, which is a large geographical unit, we cannot treat our sample as a random sample. In this case, we use fixed effects and assume that the unobserved cross-sectional effects are uncorrelated with all independent variables. According to Wooldridge (2002), fixed effects model is almost much more convincing than random effects for policy analysis using aggregated data.

4. Data and Empirical Results

This section presents the definitions and measurements of variables used in this study. The output variable used in DEA analysis is the gross output value of farming, forestry, animal husbandry and fishery deflated by agricultural price index. Five inputs are specified: land, labor, machinery, fertilizer and irrigation. [6] Land is defined as the sown area, which adjusts cultivated land for the prevalence of multiple crops per year. Labor is measured as the number of rural workers at year-end. Machinery is the total power of farm machinery, which is a proxy of capital input in agriculture production. Fertilizer is calculated in terms of volume of effective components by means of converting the gross weight of the respective fertilizers into weight containing effective component. Irrigation refers to the effectively irrigated land measured in 1000 hectares. Irrigated area is the sum of watered fields and irrigated fields where irrigation systems or equipment have been installed for regular irrigation purpose, reflecting drought resistance capacity of the cultivated land in China. Definitions of output and input variables are presented in Table 2.

<<Insert Table 2 here>>

Rural education is represented by the average years of schooling of the rural labor. Due to the limitation of publicly published data, we were unable to collect provincial-level public expenditure data on rural education. Following Fan (2002), the percentage of rural labor with different education levels is used to calculate the average years of schooling, assuming 0 years for a person who is illiterate or semi-illiterate, 6 years for primary-school education, 9 years for a junior high-school education, 12 years for a high-school education, and 14 years for college and above education.

[6]Aggregate rural labor and machinery use of agriculture, forestry, husbandry, and fisheries and forestry, is reported in the Chinese Statistical yearbooks. Consequently, inability to separate these input into different categories necessitates the analysis of the whole agriculture.

The sample consists of 22 provinces, 5 autonomous regions and 3 municipalities in mainland China from 1985 to 2011[7]. All data come from various issues of the China Statistical Yearbook, China's Agricultural Yearbook and China's Rural Statistical Yearbook.

The Data Envelopment Analysis Program (DEAP 2.1[8]) was used to calculate MPI, and its two components, namely TE and TP. A value of MPI greater than 1 implies an improvement in productivity; a value to 1 indicates the stagnation condition; while a value less than 1 is associated with a decline in productivity. The estimates of TE indicate the degree of efficiency improvement, and the estimates of TP indicate technical progress or technical regress. Similar to the findings of previous studies such as Mao and Koo (1997), Wu et al. (2001), and Chen et al. (2008), we find that China’s agricultural TFP was mainly driven by technical progress rather than from efficiency improvement. From 1985 to 2011, on average, TFP grew at an annual rate of 2.2 percent, and China experienced technical change at an annual rate of 3.9 percent; a slow-down in efficiency at an annual rate of -1.6%. Figure 1 illustrates the trend of TFP, TP and TE of China’s agriculture.

<<Insert Figure 1>>

Following the conventional geographical classification, the 30 Chinese provinces in our sample are divided into three groups, namely the eastern, middle and western regions[9]. Table 3 reports the summary of average performance of Chinese regions from the period of 1985 to 2011 in terms of TFP and its two components. As shown in Table 3, at the regional level, the changing patterns of TFP, technical progress and technical efficiency are consistent with those at the national level.

<<Insert Table 3 here>>

Using panel data covering 30 provinces in China, we investigate the relationship between rural education and productivity growth in China. Estimates of regression models are reported in Table 4. Estimation results show that the education level of rural labor significantly contributes to China’s TFP growth and technical progress, but the coefficient of Education in efficiency change ($\dot{TE}$) regression model is insignificant. These results reveal that rural education enhance agricultural total factor productivity by influencing technical progress rather than by promoting technical efficiency. The coefficient of *Education* in TFP regression model is 0.009, which indicates that the years of schooling of rural labor increase by 1 year, annual growth rate of agricultural TFP will increase by 0.009. Huang et al. (2003) stated that the rapid development of township and village

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7 Since Chongqing was once part of the Sichuan province, the data of Chongqing from 1997 to 2011 is added to those of the Sichuan province.

8 DEAP 2.1 was written by Professor Tim Coelli which could be downloadable from http://www.uq.edu.au/economics/cepa/software.htm.

9 Eastern region includes Beijing, Tianjin, Liaoning ,Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan. Central region covers Heilongjiang, Jinlin, Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan. Western region includes Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

enterprises significantly increased the opportunity cost of farming. Many rural families reallocate their resources to nonfarm activities, and many young educated rural labors no longer engage in farming, which lead to an out-migration of educated and young farmers. This could be one of the reasons for the insignificant relationship between rural education and agricultural technical efficiency. Pritchett (1996) pointed out that schooling creates no human capital, and schooling may not actually raise cognitive skills or productivity. The empirical anaylsis made by Marrocu and Paci (2012) indicated that highly educated people working in creative occupations are the most relevant component in explaining production efficiency, and noncreative graduates exhibit a lower impact. Kumar and Kubor (2014) concluded that education capital, particularly the quantity of education capital, has a significant and positive effect on TFP. However, Van Leeuwen et al. (2012) found that human capital does play a role by increasing technical efficiency rather than through general technology in Africa using Granger causality tests.

We find that the coefficients of Industry are insignificant in all three models, which suggest that the impact of industry share of GDP on agricultural productivity is not obvious. The influences of industrialization on agriculture is mixed. Industrialization might help by providing beneficial technology spillovers, better access to utilities, and improved transportation infrastructure, but meanwhile, the developing industry sector is competing with the agricultural sector for land, labor, and investment capital. China is still in the industrialization advancement. The negative externality of industrialization on agriculture production might counteract the positive effects.

The coefficient of rural labor share is negative and significant in TFP regression, which indicates that areas with more labor engaged in agriculture exhibit lower productivity. These results are consistent with our expectance. The coefficient of *rural_labor* in the TFP model is -0.036, which reveals that as the agricultural share of the rural labor decrease 1%, TFP annual growth rate will increase 0.036.

The coefficients of machine intensity are positive and significant in all regressions. These empirical results show that the popularity of mechanization can promote technical progress and technical efficiency, and enhance total factor productivity.

To reflect the effect of weather condition, the percentage of natural disaster affected areas to total cultivated area is included in the regression models. The coefficients of affect in TFP regression and TE regression are both negatively significant, which means that the natural disaster reduces TFP and TE.

The variable of time trend is positively and significant with TFP growth rate, which indicates that China is experiencing continuing increase in productivity, but the increasing trends are not found in TP and TE growth.

5. CONCLUSIONS

In theory, education is expected to accelerate agricultural productivity by enhancing the productive capabilities of all producers by exposing them to a more systematic and dynamic production system and by enhancing their ability to choose the optimal levels of inputs and outputs (Welch 1970). Since the green revolution swept across the world, agricultural technological has mainly involved with the generation and dissemination of new crop varieties and the use of chemical fertilizer.

In the present study, we attempt to apply these theoretical insights to the case of China's agricultural production. With provincial-level aggregate data, we first used non-parametric method to measure total factor productivity change in China, and then we decompose the overall productivity change into technical change and efficiency change. On average, China experienced TFP growth at an annual rate of 2.1 percent, technical change at an annual rate of 3.8 percent and a slow-down in efficiency at an annual rate of -1.6% from 1985 to 2011. This suggests a large unused potential (i.e. low technical efficiency) in China's agricultural production. And then, we examine the relationship between rural education and productivity, using a panel dataset covering 30 Chinese provinces from the period 1985 to 2008 to investigate the impact of rural education on productivity growth of China. The results indicated that the development of rural education plays positive role on China's agricultural productivity growth. Furthermore, in order to better identify the channels through which rural education development influence productivity, we also investigate the impact of rural education on the growth rates of two components of TFP (i.e. technical efficiency and technical progress). Empirical results show that rural education enhances agricultural total factor productivity through technical progress rather than by raising technical efficiency. The findings support the hypothesis of Nelson and Phelps that education plays an important role in adopting and utilizing technologies and clarifies its role in the process of growth. However,

We also find evidence that provinces with higher intensity of mechanization tend to performance better on TFP, technical progress and technical efficiency. These findings have important policy implications to China's agricultural development. The Chinese government should make great strides in providing financial aid and better equipment to rural education. Substantial investment in research and development on agriculture improved production technology. In order to allow more smallholder farmers to capture the benefits of available advancing technologies, much more investment in applied R&D and educational program is needed. In the era of internet, distance education could play crucial role on farmer education and disseminating knowledge. There is a need to improve the skills and knowledge of research and extension personnel by on-farm training, seminars, study visits and publications. Rural education should contribute towards rural development, hence a wide range of education including basic education, vocation education and adult education should all be developed. Rural education is not just about training some very bright kids who then leave rural areas to go to urban schools, as they will not contribute to rural development.

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Table 1 Definitions of Variables in regression Model

Variable	Definitions (Unit)
$\dot{TFP}$	Growth rate of total factor productivity
$\dot{TP}$	Growth rate of technical progress
$\dot{TE}$	Growth rate of technical efficiency
Education	Average years of schooling of the rural labor (years)
Industry	the industry share of GDP,
Rural labor	the agriculture's share of the rural labor force
Machine intensity	Mechanical power/agricultural labor (kw/person).
Affected	Natural disaster affected area/Cultivated are
T	Time trend （T=1, the beginning year, t=2, the 2nd year, ….）

Table 2 Definitions of Variables in DEA_Malmquist Model

Variable	Definitions (Unit)
Output	The gross output value of farming, forestry, animal husbandry and fishery (100 million RMB) deflated by agricultural price index.
Land	The sown area (1000 ha)
Labor	the number of rural workers at the year-end (10,000 persons)
Machinery	The total power of farm machinery (10,000 kw).
Fertilizers	The volume of effective components by means of converting the gross weight of respective fertilizers into weight containing effective component. (1000 kg)
Irrigation	The sum of watered fields and irrigated fields where irrigation systems or equipment have been installed for regular irrigation purpose (1000 ha).

Table 3 Average Annual Changes of TFP, TP and TE in China, 1985-2011

Region	TFP change	Technical Change	Efficiency Change
National	1.022	1.039	0.984
Eastern Region	1.044	1.051	0.993
Central Region	1.018	1.041	0.978
Western Region	1.001	1.027	0.976

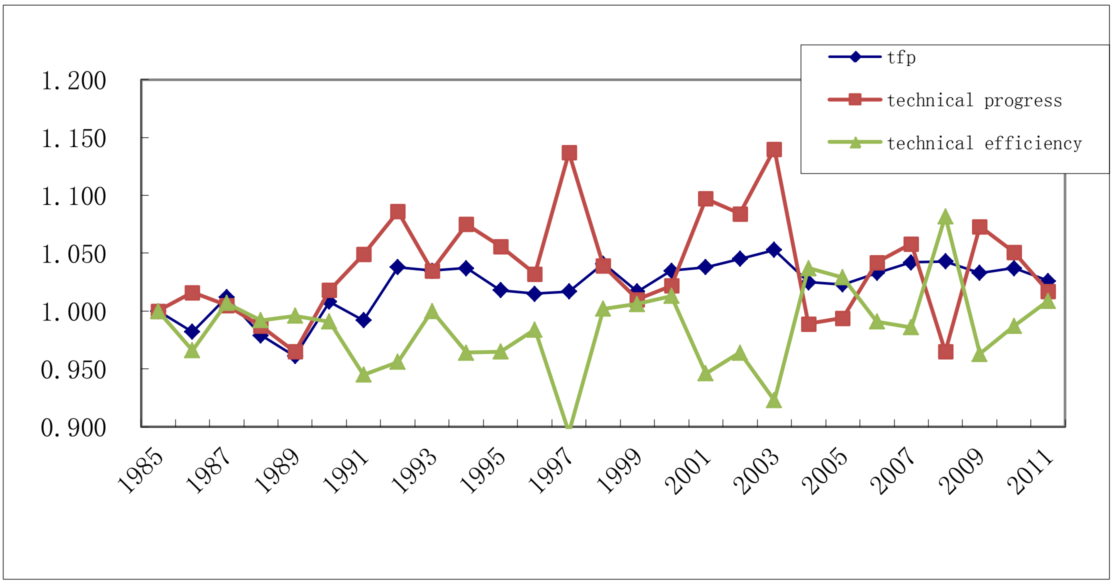
Source: Calculated by authors.

Table 4 Estimates of the Regression Model

Independent Variables	Dependent Variables		
	$\dot{TFP}$	$\dot{TP}$	$\dot{TE}$
Constant	1.008^{***} (40.550)	1.007^{***} (48.217)	1.027^{***} (38.949)
Education	0.009^{***} (4.241)	0.007^{***} (4.347)	0.001(0.381)
Industry	-0.024(-0.858)	0.019(0.864)	-0.038(-1.317)
Rural_labor	-0.036^{**} (-2.009)	-0.021(-1.362)	-0.024(-1.275)
Machine_ intensity	0.001^{***} (3.396)	0.005^{***} (3.148)	0.004^{**} (2.165)
Affected	-0.064^{***} (-4.605)	-0.003(-0.718)	-0.080^{***} (-5.553)
T	0.001^{*} (1.883)	-0.000(0.000)	0.000(0.000)
Adjusted R-squared	0.966	0.991	0.971

Note: 1. ***, ** and * represent statistical significance at the 1 percent, 5 percent and 10 percent level, repectively. For all regressions, the t-statistics values are presented in parentheses. 2. Estimated coefficients of cross-sectional fixed effect are omitted for each observational unit. 3. Estimates of cross sectional interceptions are omitted.

Figure 1 Annual change of TFP, annual TP change and annual TE change in China, 1985-2011



Source: Calculated by authors.