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China's Regional Agricultural Productivity Growth: Catching Up or Lagging Behind[1]

Sun Ling Wang[2]
(USDA-Economic Research Service, USA)

Jikun Huang and Xiaobing Wang
(School of Advanced Agricultural Sciences, Peking University, China)

Francis Tuan
(Renmin University of China, China, and East Asia Economic Consulting, USA)

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[2] Corresponding author, email address: slwang@ers.usda.gov

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Abstract

In this study, we use a multilateral total factor productivity (TFP) panel data, spanning 1985-2011 period, to test the hypotheses of convergence to a single TFP level (σ convergence) or to a region-specific steady state TFP growth rate (β convergence) for China's farm sector. Results show that there is no evidence of an overall σ convergence across all provinces. However, we find robust evidences of β convergence. Estimated rates of β convergence are conditional on how we capture the heterogeneity across regions. Overall, the rate of β convergence ranges from 0.016 to 0.028. Estimates also show that higher growth rate of education, R&D, capital/labor ratio, or intermediate goods/labor ratio can boost the rate of TFP growth.

Key words: Total Factor Productivity (TFP), σ convergence, β convergence, multilateral comparison, China agricultural sector.

JEL codes: O13, O47, Q16

I. Introduction

The existing literature reaches a consensus that Chinese economic development in recent years can be summarized with two characteristics: rapid growth of the national economy and widening interregional disparity (Chen and Fleisher, 1996; Fan and Zhang, 2002; Groenewold et al., 2008; Chen, 2010; Fan et al., 2011 among others). China implemented a series of rural reforms and open policies since 1978 and has demonstrated strong economic growth afterwards. The growth rates of China's real gross domestic product (GDP) averaged around 10% per annum between 1978 and 2014 (World Bank, 2015), the highest in the world during that period. Total domestic production of cereal and coarse grains also experienced dramatic growth, from 359 million tons

in 1980 to more than doubled 782 million tons in 2014, and held relatively stable shares of global output, ranging from 16% in 1980 to 19% in 2014. Nevertheless, the gains from past reforms seem to be distributed unequally among regions. For example, in early 2010s per capita GDP in the inland region is less than half of that in the coastal regions. If measured by per capita income, both rural and urban residents in the inland regions earned only about two-thirds of their counterparts in the coastal regions. (National Bureau of Statistics of China (NBSC), 2015).

Regarding the growth of China agricultural sector, Chen et al. (2008) showed that regional disparities in agricultural productivity growth have worsened over the period 1990–2003 based on Malmquist productivity index measures. On the other hand, while Wang et al. (2013) found that China agricultural productivity growth across regions is strong but uneven, provinces with the most rapid productivity growth included a mix of coastal regions that led China's economic development and several western provinces with lower total factor productivity (TFP) levels for the period 1985-2007. To narrow down the rising inequalities, in 2005, China launched an explicit objective of "harmonious development" to balance development across regions, and implemented several related projects since—including the large-scale western development, the rejuvenation of the northeastern region, and the booming-up of the central region. However, it is not clear that if the gap of agricultural TFP levels between China's most productive regions and those lagged behind is narrowing down or widening up since China's rural reform and in recent years.

Economic theories suggest that the rates of economic growth tend to converge across countries or regions in the long run the empirical test results are ambiguous (see Barro and Sala-i-Martin (1995), Temple (1999), Kumar and Russell (2002), Furceri (2005), Poudel, Paudel, and Zilberman (2011) for more discussions). Although there are much studies examining the

convergence hypotheses using cross-country or cross-industry data or agricultural data from developed countries there is little attention on investigating China's agricultural productivity convergence issue. Given China's critical role in global food market and its rising disparity across regions it is important to understand whether agricultural productivity convergence hypothesis holds in China, an economy—with large population and territory—still in transition. Especially, agricultural revenue still accounts for a relevant share of family income in less-developed or poor regions. In this study, we test the hypotheses of agricultural TFP convergence and catch-up effect for China's farm sector. We also examine the potential factors that could affect the speed of catch-up. The existence of convergence implies improvement of disparity across regions. However, in a case of widened TFP gap it will have important policy implications for the development of region-specific plans, to stimulate the catch-up process in the farm sector.

Based on diminishing returns to capital assumptions, Neo-classical growth theory (Solow (1956)) predicts that an economy with a lower capital-labor ratio will have higher marginal product of capital and therefore grow faster and converge to the steady state of those with a higher capital-labor ratio. This is also known as the absolute convergence. Barro and Sala-i-Martin (1990) characterized two types of convergence: one is σ-convergence as when the dispersion of relative per capita income or output across economies or regions decrease over time; and the other is β-convergence as when poor economies or regions grow faster than rich ones—a "catching up" effect. Later in Barro and Sala-i-Martin (1991) they discussed a form of conditional β convergence in that an economy with a lower starting level of per capita output will have a higher per capita growth rate. In this case the convergence can be held within groups of economies with similar characteristics. Using U.S. farm sector data several studies examine the hypothesis of TFP

convergence across the states (McCunn and Huffman (2000), Ball, Hallahan, and Nehring (2004), Ball et al. (2013)). McCunn and Huffman found evidence of "catching-up" (β-convergence) in state agricultural TFP but rejected the hypothesis of declining cross-sectional dispersion (σ-convergence). Ball, Hallahan, and Nehring (2004) and Ball et al. (2013) also found evidences of β-convergence after controlling for variables that capture regional differences. As to China agricultural sector, McErlean and Wu (2003) found that labor productivity diverges between 1985 and 1992, but converges between 1992 and 2000 in China's farm sector. On the other hand, based on data envelopment analysis (DEA) approach Li et al. (2008) found sigma convergence existed in Chinese agricultural productivity for the 1980-2005 period. Since labor productivity can be affected by adding other inputs and not necessarily reflect the level technology advancement and DEA approach only provide information on rate of growth but not the relative level and therefore does not allow us to test for the β convergence this study use a panel of multilateral TFP estimates to examine the productivity convergence issue for China's farm sector.

The remainder of the paper is organized as follows. Section II describes the methods of measuring σ and β convergences. Section III presents the multilateral TFP measures and introduces variables that may affect the speed of convergence, as well as the data sources. Section IV briefly discusses the TFP estimates and the sources of agricultural output growth for the period 1985-2011. Section V discusses the results of convergence tests. Finally, we summarize our main findings along with their policy implications in the summary and conclusion section.

II. Methods

In this study we conduct three types of convergence test. First, we test for σ convergence, the unconditional convergence. The hypothesis is held if the dispersion of TFP across regions reduces over time (Lichtenberg (1994)). We consider the following regression model:

$$Var(lnTFP_t) = \emptyset_0 + \emptyset_1 t + \epsilon_t \qquad (1)$$

where $Var(lnTFP_t)$ is the variance of *TFP* across regions at time t, and ϵ_t is the random disturbance with zero mean and constant variance. There is a σ convergence if $\emptyset_1 < 0$ (Lichtenberg, McCunn and Huffman (2000)). We conduct σ convergence tests using a TFP panel of full sample and TFP panels of seven sub-regions clustered by province's geographical location and economic region—East, Middle, North, Northeast, Northwest, South, and Southwest regions.

Second, we test for β convergence. The hypothesis is that provinces with lower TFP at the start of each sub-period tends to grow faster. We consider the following regression model using average rate of TFP growth over the interval T (Barro and Sala-i-Martin (1991), McCunn and Huffman (2000)):

$$\left(\frac{1}{T}\right) \cdot ln\left(\frac{TFP_{i,t+T}}{TFP_{i,t}}\right) = \alpha_0 - \frac{(1-e^{-\beta T})}{T} \cdot \ln(TFP_{i,t}) + u_{it} \quad (2)$$

where *i* indexes the province, *t* indexes time, TFP_{it} is *TFP* for province *i* at time *t*, T is the length of the observation interval (following Barro and Sala-i-Martin we use 5 years as the interval), the coefficient β is the rate of convergence, u_{it} is an error term with zero mean and constant variance. There is a β convergence if $\frac{(1-e^{-\beta T})}{T}$ >0. Since T > 0 the necessary condition for a β convergence is $e^{-\beta T}$<1, that requires a positive β. If β convergence exists then when interval T gets larger, TFP growth rate will move toward the steady state growth rate, α_0. This kind of β convergence is also referred to absolute β convergence. To simplify the expression of equation (2) we replace the

notation of average TFP growth rate over the interval T with $\dot{TFP}$, and substitute the coefficient of $\ln(TFP_{i,t})$ with $-\hat{b}$ that

$$-\hat{b} = -\frac{(1-e^{-\beta T})}{T} \qquad (3)$$

Equation (2) can then be rewritten as:

$$\dot{TFP}_{it} = \alpha_0 - \hat{b} \cdot \ln(TFP_{it}) + u_{it} \quad (4)$$

Once the $\hat{b}$ coefficient is estimated we can then recover the β convergence coefficient from equation (3).

Third, we test for conditional β convergence. According to literature, exiting economy or region specific conditions may also affect the rate of convergence or even result in a divergence situation. McCunn and Huffman suggest that the rate of β convergence can be related to R&D and farmers' educational attainment using a linear expression. Ball et al. (2004, 2013) argue that the relative ratios of capital (K) and intermediate goods (M) to labor (L) can also affect agricultural TFP growth rate through embodied technical change and therefore affect β convergence. They suggest to conduct β convergence test with state specific variables as control variables, such as the growth rates of K/L and M/L. In recent growth literature "openness" through trade is also considered as a factor influencing technology spillover and TFP growth. We suspect relaxed restrictions on foreign trade policy may have enhanced agricultural productivity by providing access to new technology and new markets. We consider a few specifications with alternative provincial level control variables, including rates of population with higher education (Education), number of regional research and development staffs (R&D), K/L and M/L ratios, and relative export share—to test for the sensitivity and robustness of β convergence coefficient and potential impacts of those control variables on regional TFP growth. We consider the following general form:

$$\dot{TFP}_{it} = \alpha_0 - \hat{b} \cdot \ln(TFP_{it}) + \sum_{j=1}^{\tau} \gamma_j \dot{Z}_{j,it} + u_{it} \quad (5)$$

where *i* indexes the province, t indexes time, $\dot{TFP}_{it}$ is the average TFP growth rate over the interval *T* for province *i*, TFP_{it} is *TFP* for province *i* at time *t*, $\dot{Z}_{j,it}$ is the average growth rate of control variable *j* over interval *T* for province *i* at time *t*, u_{it} is the disturbance term with zero mean and constant variance.

III. Data sources and measurement

Total factor productivity

One requirement for conducting β convergence test is that the dataset needs to be a panel of relative TFP levels to allow us to incorporate the initial TFP level within each time frame in the estimation. For this purpose, we employ a multilateral TFP panel data in our analysis. We follow the approach proposed by Caves, Christensen, and Diewert (1982, CCD thereafter) and the application of Wang et al. (2013) for China's provincial agricultural TFP construction. We extend Wang et al.'s China agricultural TFP panel data to 2011[3] to provide more up-to-date information. To reflect the changes in the arable land updates of the 2006 China agricultural census (China Statistical Yearbooks) we also revised TFP estimates back to 2006. The details of the measurement on output and inputs—capital, labor, intermediate goods, and land can be found in Wang et al. In this section our discussion only focuses on the construction of transitive multilateral comparisons of output, inputs, and TFP.

TFP is an estimate of the ratio of total real output (Y) over total real input (X). Therefore, TFP is a productivity measure that takes account of the use of all inputs to the production process. We adopt the Törnquist-Theil (TT) index as an approximation of the Divisia index to

[3] Original data covers the period of 1985-2007.

capture the TFP changes for a specific province between two discrete points in time, using average shares from two time points as the weighs for inputs or outputs. Thus, the implicit quantity estimate using a TT index is based on the rolling weights that can accommodate any substantial changes in relative prices over time. Based on the growth of aggregated output and input, the growth rate of total factor productivity (TFP) growth between two subsequent periods of time can be expressed as the difference between these two indexes:

$$ln(\frac{TFP_t}{TFP_{t-1}}) = \sum_m \frac{1}{2} * \left(R_{m,t} + R_{m,t-1}\right) * \ln\left(\frac{Y_{m,t}}{Y_{m,t-1}}\right) - \sum_n \frac{1}{2} * \left(W_{n,t} + W_{n,t-1}\right) * \ln\left(\frac{X_{n,t}}{X_{n,t-1}}\right) \quad (5)$$

where *lnTFP* is the natural log of the TFP index; R_m's are the shares of output *m* in total revenue and W_n's are the shares of input *n* in total cost at time *t* and *t-1*, respectively; Y_m's and X_n's are the quantities of output *m* and input *n* at time *t* and *t- 1*, respectively.

As to the construction of multilateral output, inputs, and TFP estimates, CCD proposed a methodology using superlative index numbers. Under the CCD framework the translog multilateral output, input, and productivity indices are all transitive. Therefore, we can construct a normalized multilateral TFP index using any region as the base region. TFP index between region *k* and the base region *l* can be obtained by estimating the following equation:

$$\ln(\frac{TFP_k}{TFP_l}) = \frac{1}{2}\sum_i (R_m^k + \overline{R}_m) * \ln(\frac{Y_m^k}{\tilde{Y}_m}) - \frac{1}{2}\sum_i (R_m^l + \overline{R}_m) * \ln(\frac{Y_m^l}{\tilde{Y}_m}) - \frac{1}{2}\sum_n (W_n^k + \overline{W}_n) * \ln(\frac{X_n^k}{\tilde{X}_n}) + \frac{1}{2}\sum_n (W_n^l + \overline{W}_n) * \ln(\frac{X_n^l}{\tilde{X}_n})$$

(6)

where a bar indicates the arithmetic mean and a tilde indicates the geometric mean, R_m is the revenue share for output *m*, W_n is the cost share for input *n*. We first construct multilateral price indexes for output and inputs based on the CCD approach. The index of real output (or real input) between two provinces is obtained by dividing the nominal output (or input) value ratio for two provinces by the corresponding output (or input) price index. The multilateral output,

inputs, and TFP indexes are extended to 2011 for China's twenty-five contiguous provinces[4] using Anhui province as the base province, and 1994 and the base year. Relative TFP levels for other provinces and other years are normalized to 1994 Anhui TFP level. The result is a "true" panel with both temporal and spatial comparability.

The data of quantities, prices for individual output and input as well as the total revenue, or expenditure data are drawn from various sources, including National Agricultural Product Cost and Revenue Survey Data Books, China Animal Husbandry Yearbooks, China Rural Statistical Yearbooks, and China Statistical Yearbooks in various years (see Wang et al. (2013) for more details).

Control variables

We include a number of control variables—education (Edu), R&D, relative input factor ratios (capital/labor (K/L) and intermediate goods/labor (M/L)), export (Ex) in our tests of the catch-up hypothesis (β convergence) to capture the heterogeneity that may affect the speed of catch-up between provinces. Education variable is measured as the percentage of total rural labor with an educational background of at least with senior secondary schooling. Since there is no R&D expenditure data at provincial level R&D variable is measured using the total number of staffs who work on research in agricultural research institutions as proxy. China's agricultural R&D system is a public system, large in size but also decentralized (Huang and Rozelle (2014), Babu, Huang, and Zhang (2016)). Each province has its regional agricultural research institutions (e.g., provincial agricultural university, academy of agricultural sciences at provincial and prefectural

[4] We use the term "provinces" for all of the provinces and autonomous regions. The twenty-five provinces include Anhui, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan (Chongqing municipality is combined with Sichuan), Xinjiang, Yunnan, and Zhejiang. We excluded three province-level municipalities (Beijing, Tianjin, and Shanghai), one island province (Hainan) and one autonomous region (Tibet) as their output is small and data are not available for all years.

levels). We assume that a greater pool of research staffs may deliver more research outputs that can contribute to local agricultural productivity growth more directly and instantaneously. However, given that the R&D staffs data is only available for the period 1988-2005 at provincial level we conduct our convergence tests using a smaller sample with shorter time period when incorporating R&D variable in the regression models. Export is measured as the share of provincial agricultural export in total agricultural export. Given that the provincial agricultural export data is only available in the post-1992 period we conduct our convergence tests using a smaller sample with shorter time period when incorporating export variable in the regression model. K/L and M/L are measured using the input estimates at provincial level. Data sources include China Science and Technology Statistical Yearbook, China Rural Statistical Yearbook, and China Statistical Yearbook in various years.

Data description

We present a summary table of the descriptive statistics of control variables by region in Table 1. As we suspected the differences of those control variables within region and across regions are quite large. For example, the average growth rates of population who have at least a high school educational background ($\Delta\ln(Ed)$) is much higher for the Northwest region than for others. However, the dispersion of the education variable within the Northwest region is also high, about three to seven times of the dispersion status in other regions. The means of the annual growth rate of the intermediate goods to labor ratio ($\Delta\ln(M/L)$) are rather close across regions ranging from 0.054 to 0.073, compared to that of annual growth rate of capital to labor ratio ($\Delta\ln(K/L)$), which ranged from 0.04 to 0.52 during the study period. The main reason may be due to the higher cost of capital investment that is less affordable for poor areas, which are already left behind. Still, the dispersions of those two variable are also high within each region implying that some provinces

have less rates of change in M/L and K/L ratios than their neighboring provinces. As to the growth rate of the R&D variable (Δln(RD)) the negative means of that variable across regions indicate research staffs were downsized for many provinces and periods of time. Still, the maximums of the average growth rates are still quite high in some provinces. The average annual growth rates of relative export ratios varied across regions and within region that the minimum and maximum of that variable ranged from -1.516 in the Middle region to 1.368 in the same region. We incorporate these variables in the convergence tests to control for the heterogeneity across provinces.

(Insert table 1 here)

IV. Econometric results of convergence tests

We present results of three types of convergence tests—σ convergence test, absolute β convergence test, and conditional β convergence test that take into account the effects of region-specific characteristics.

σ convergence tests

In addition to the standard σ convergence test some literature present a stochastic convergence test that is related to the unit root hypothesis (Bernard and Durlauf (1995), Carlino and Mills (1996)). The stochastic convergence test is based on an assumption that deviations in relative productivity are temporary, which therefore rules out deterministic or stochastic trends. Under this conceptual framework a stochastic convergence test involves the form of a regression model of augmented Dickey-Fuller test (ADF test), and the evidence of a unit root indicates no convergence. Following this concept we first conduct unit root test based on ADF test, Phillips-Perron (PP) test, and Zivot-Andrews (Z-Andrews) test, where Z-Andrews test allows for a structural break, using time series of annual cross-sectional variances of provincial TFP in the

full sample, as well as subsamples clustered by geo-econ regions (table 2). Results show that both Northwest region and South region reject the hypothesis of unit root without trend, showing evidence of stochastic convergence. According to Z-Andrews test, after considering intercept structural break, both Middle region and Southwest region also demonstrate stochastic convergence. There is no evidence of stochastic convergence for other regions since either a time trend is required to hold the time series stationary or we cannot reject the hypothesis of unit root with or without including time trend in the test.

(Insert table 2 here)

We then conduct standard σ convergence tests for all twenty-five provinces and for each geo-econ group by regress annual cross-sectional variances of provincial TFP levels[5] with time trend. We fit equation (1) with OLS estimation (table 3). According to the results while the coefficients of time trend are negative for the Northwest region and the South region they are not statistical significant. As to other regions since the coefficients of time trend are significantly positive there is no evidence of σ convergence but, instead, divergence over time. After consider structural break based on Z-Andrews tests the time trend coefficient for East, Middle, and Northeast regions are all negative but not statistical significant. Therefore, based on all σ convergence test results above there is no robust evidence showing an overall *σ* convergence for agricultural TFP across all regions. However, hypothesis of stochastic convergence holds for a few regions based on unit root test results.

(Insert table 3 here)

Panel unit root test

[5] Provincial TFP levels are normalized to 1994 Anhui TFP level so that 1994 Anhui TFP level equals 1.

Before investigating the hypotheses of absolute β convergence and conditional β convergence we first examine if each variable in equations (2) and (3) are stationary to avoid spurious regression results. We conduct panel unit root tests using approaches proposed by Levin, Lin, and Chu (LLC test, 2002) and Im, Pesaran, and Shin (IPS test, 2003). According to the results from both LL test and IPS test (table 4) we reject the unit root hypothesis for all variables except the growth rate of capital labor ratio (K/L). The possible reason for the economic behavior of this variable may be due to the persistent decline of farm labor in most provinces and the increasing capital investment that started from almost nothing before China's rural reform and its economy taking-off after the 1980s. China's farm sector has gradually transformed from a labor intensive industry to less labor dependency by substituting part of its farm labor with farm machinery work and adopting more intermediate goods, such as agricultural chemicals. We keep the original form of K/L growth rate variable in one of our estimated model specification (Model 4) to preserve its economic meaning and make comparisons with other model estimates for the robustness check for β convergence coefficient.

(Insert table 4 here)

β convergence tests

We first conduct absolute β convergence tests by fitting equation (2) with a panel of full samples using fixed effect model estimation. The test result is presented in table 5 as Model 1. The negative and significant sign confirm the existence of an absolute β convergence. The β convergence coefficient is 0.016. It is smaller than that estimated by McErlean and Wu based on China's agricultural labor productivity data. It is also smaller than the rate of convergence based on U.S. TFP data estimated by McCunn and Huffman and Ball et al.

(Insert table 5 here)

We then consider other control variables to capture heterogeneity across regions. We include education variable and R&D variable in model 2. Results show that both variables significantly and positively affect provincial TFP growth rates. After controlling for these two variables the conditional rate of β convergence increases to 0.018. We further examine the hypothesis of embodied technical change through uses of capital goods and other intermediate goods in Model 3 and Model 4. Both M/L growth rate and K/L growth rate have positive and significant impacts on TFP growth grate. However, after controlling for these two variables the rates of conditional β convergence do not differ much from that without considering these two variables (Model 2). We then drop the variable of K/L growth rate and replace with provincial agricultural export share in national total export. While the coefficient estimate of export variable is not statistically significant the rate of conditional β convergence increases to 0.024. Model 6 include all control variables considered above. Results show that export variable is still insignificant, and yet, rate of conditional β convergence is boosted to 0.028.

In sum, results of β convergence tests confirm the catch-up hypothesis that there is an inverse relation between the rate of productivity growth and its initial level of relative TFP to Anhui province. However, unequally distributed R&D resources, different levels of human capital embodied in labor force and different levels of embodied technology through capital investment or use of agricultural chemicals and others intermediate goods can all affect the rate of convergence across regions.

Summary and Conclusions

China is a developing country with a big population and a large territory. Interregional economic disparity is becoming a serious problem. In this study we investigate hypotheses of agricultural

TFP σ convergence and β convergence for China's farm sector using a panel of twenty-five provinces, spanning the period 1985-2011. Results show that there is no evidence of an overall σ convergence across all provinces. Yet, regions of the Northwest, the South, and the Southwest demonstrate stochastic σ convergence within each region over the observed period. On the other hand, results of β convergence tests confirm an absolute β convergence and a conditional β convergence. The inverse relation between the rate of TFP growth and for specific province and its TFP initial level reveals a catch-up effect for those left behind. Estimated rates of β convergence are conditional on how we capture the heterogeneity across regions. After we control for more variables the rate of β convergence is also accelerated. Overall, the rate of β convergence ranges from 0.016 to 0.028.

Regression results also show that a higher growth rate of each of the control variables—education, R&D, relative capital/labor ratio, and relative intermediate goods/labor ratio—can boost the rate of TFP growth over time, except the growth rate of provincial agricultural export share. An unequally allocated resources of research and human capital can hinder the rate of convergence. Higher rate of growth of the relative level of intermediate good and capital investment can enhance TFP growth. However, the proxy of openness variable—agricultural export share in national export—does not have a significant impact on China's agricultural productivity growth.

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Table 1 Descriptive Statistics on individual control variables by region

Region	Δln(Ed)				Δln(M/L)				Δln(K/L)				Δln(RD)				Δln(export)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
East	0.040	0.025	-0.027	0.104	0.073	0.059	0.001	0.558	0.044	0.056	-0.019	0.224	-0.034	0.039	-0.177	0.032	0.014	0.078	-0.238	0.151
Middle	0.071	0.071	-0.038	0.193	0.076	0.024	0.038	0.117	0.045	0.032	-0.011	0.088	-0.036	0.028	-0.109	0.027	-0.045	0.367	-1.516	1.368
Northeast	0.013	0.024	-0.033	0.066	0.060	0.047	-0.062	0.130	0.052	0.094	-0.076	0.375	-0.039	0.040	-0.134	0.033	-0.009	0.141	-0.370	0.293
Northwest	0.228	1.035	-4.098	3.985	0.054	0.035	-0.038	0.134	0.004	0.066	-0.134	0.180	-0.031	0.023	-0.081	0.009	-0.038	0.123	-0.273	0.189
North	0.027	0.022	-0.051	0.062	0.075	0.046	-0.072	0.206	0.030	0.042	-0.016	0.176	-0.035	0.041	-0.203	0.126	-0.020	0.095	-0.174	0.240
Southwest	0.074	0.096	-0.149	0.288	0.065	0.030	-0.004	0.123	0.039	0.049	-0.040	0.148	-0.034	0.039	-0.093	0.062	-0.042	0.063	-0.218	0.058
South	0.035	0.016	-0.004	0.059	0.061	0.041	-0.015	0.174	0.033	0.039	-0.023	0.120	-0.028	0.029	-0.084	0.019	-0.055	0.061	-0.212	0.041

Source: Authors' calculation.

Table 2. Results of unit root test

Variables	ADF test statistics		Phillips-Perron test		Zivot-Andrews test		break
Var(lnTFP_all)	-3.436	*[a]	-4.014	**[a]	-5.027	***[a]	1990
Var(lnTFP_East)	-2.957		-2.928		-4.65	**[a]	1998
Var(lnTFP_Middle)	-2.547		-2.458		-8.784	***	2002
Var(lnTFP_North)	-3.449	*[a]	-3.463	*[a]	-4.729	**[a]	1990
Var(lnTFP_Northeast)	-2.185		-2.261		-4.725		1998
Var(lnTFP_Northwest)	-3.102	**	-3.226	**	-4.176		1993
Var(lnTFP_South)	-4.161	***	-4.126	***	-5.766	***	1990
Var(lnTFP_Southwest)	-2.8		-2.788		-5.112	**	1990

Source: Authors' calculation.

Note 1: 'Var' indicates variance of the variable within the parenthesis.

Note 2: '*' indicates significant at 10% level; '**' indicates significant at 5% level; '***' indicates significant at 1% level.

Note 3: 'a' indicates the unit root test is conducted with a time trend.

Table 3. Results of σ convergence test

	without structural break				with structural break							
Regions	trend coefficient	t statistics		adj-R^2	trend coefficient	t statistics		break coefficient	t statistics		adj-R^2	break
All regions	0.0042	4.13	***	0.422	0.0070	1.02		-0.0025	-0.41		0.398	1990[a]
East	0.0021	4.01	***	0.406	-0.0005	-0.51		0.0020	2.82	**	0.554	1998[a]
Middle	0.0021	1.45		0.047	-0.0019	-0.95		0.0780	2.64	**	0.258	2002[b]
North	0.0123	14.03	***	0.899	0.0149	2.51	**	-0.0023	-0.44		0.895	1990[a]
Northeast	0.0040	3.91	***	0.394	-0.0022	-1.71		0.0972	5.65		0.755	1998[b]
Northwest	-0.0015	-0.90		-0.009				NA				
South	-0.0013	-0.59		-0.031				NA				
Southwest	0.0042	3.79	***	0.379	0.0082	8.17		-0.0909	-5.62		0.747	1990[b]

Source: Authors' calculation.
Note 1: 'a' indicates the break is a trend break, and 'b' indicates the break is an intercept break.
Note 2: '*' indicates significant at 10% level; '**' indicates significant at 5% level; '***' indicates significant at 1% level.
Note 3: 'NA' indicates no break is included in the estimates as the variance variable is stationary at 1-5% significance level based on ADF and P-P tests.

Table 4. Results of panel data unit root tests

Variables	Levin and Lin's Test Statistics		Im, Pesaran, and Shin's Test Statistics	
lnTFL level	-7.2061	***[a]	-6.0995	***[a]
TFP growth rate	-6.1498	***	-4.3631	***
Hi-Ed growth rate	-7.4188	***	-4.0977	***
RD staffs growth rate	-5.5	***[a]	-3.554	***[a]
(K/L) growth rate	0.6315	[a]	4.5207	[a]
(M/L) growth rate	-5.2574	***	-3.5396	***
Export share growth rate	-5.9085	***	-1.4789	

Source: Authors' calculation.
Note 1: 'K/L' indicates Capital/Labor ratio, 'M/L' indicates Materials/Labor ratio, 'Hi-Ed' indicates share of total population with an educational background of high school or above.
Note 2: '*' indicates significant at 10% level; '**' indicates significant at 5% level; '***' indicates significant at 1% level.
Note 3: 'a' indicates the unit root test is conducted with a time trend.

Table 5. Results of regression models on TFP growth rates

Variables	Model 1			Model 2			Model 3			Model 4			Model 5			Model6		
	coefficients	t-statistics		coefficients	t-statistics		coefficients	t-statistics		coefficients	t-statistics		coefficients	t-statistics		coefficient	t-statistics	
Dependent variable: TFP average growth rate																		
Constant	0.0228	13.18	***	0.0286	15.97	***	0.0161	5.91	***	0.0149	5.38	***	0.0184	5.16	***	0.0176	5.04	***
lnTFP	-0.0762	-9.89	***	-0.0864	-11.47	***	-0.0836	-11.67	***	-0.0875	-11.82	***	-0.1122	-8.67	***	-0.1292	-9.27	***
Hi-Ed share growth rate				0.0200	7.41	***	0.0177	6.86	***	0.0175	6.81	***	0.0102	2.06	**	0.0094	1.95	**
RD staffs growth rate				0.2140	5.69	***	0.2272	6.36	***	0.2046	5.47	***	0.2195	5.03	***	0.1814	4.06	***
(M/L) growth rate							0.1977	5.88	***	0.1731	4.84	***	0.1855	3.98	***	0.1201	2.36	**
(K/L) growth rate										0.0590	1.95	**				0.1030	2.95	***
Export share growth rate													0.0012	0.894		-0.0006	-0.07	
calculated β	0.0159			0.0181			0.0175			0.0183			0.0238			0.0277		
F statistics		71.77	***		76.79	***		72.75	***		59.52	***		24.39	***		22.59	***

Source: Authors' calculation.

Note 1: 'M/L' indicates Materials/Labor ratio, 'Hi-Ed' indicates share of population with an educational background of high school or above.

Note 2: '*' indicates significant at 10% level; '**' indicates significant at 5% level; '***' indicates significant at 1% level.