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Are China's regional agricultural productivities converging: How and why?☆

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ABSTRACT

This article tests the hypotheses of convergence to a single level of total factor productivity (TFP), and a steady state of TFP growth rate in China's agricultural sector. Based on multilateral TFP estimates we found that China's agricultural sector has rebounded in recent years from a slower TFP growth in the 2005–2007 period. While convergence test results confirm a "catch-up" effect that provinces with lower TFP levels tend to grow faster than others, estimated rates of β convergence are conditional on how we capture the heterogeneity effect across regions. The rates of β convergence range from 0.016 to 0.039 under different model specifications. Estimates show that higher growth rates of educational attainment, R&D, and intermediate goods density (per unit of labor) can enhance TFP growth. Unfortunately, there is no evidence of an overall σ convergence, indicating that TFP levels are not converging except in the South region. It implies that to catch up with leading provinces, it would require extra efforts for those lagging behind by increasing their region-specific research investment, promoting rural educational attainment, and enhancing embodied technical change.

1. Introduction

China's rural reforms and open policies since the early 1980s have transformed the country from a closed economy with sluggish growth into a fast-growing open economy (Huang and Rozelle, 2018; Tuan, 2015; Gale, 2013; Lin, 1997). Its real GDP grew at an average rate of 9.8% per year between 1980 and 2015 (World Bank, 2017), the highest among all countries during that period. Agricultural output value in real term also grew strongly at an average annual rate of 5.4% in the last four decades (NBSC, 2015). To pursue sustainable agricultural growth, China has intensified its agricultural research investment in the last two decades. As a result, in 2009 its public agricultural research investment surpassed the U.S. for the first time (Clancy et al., 2016).

Despite the rapid growth of agricultural production and farmers' income in China, the nation has faced challenges of unbalanced growths among regions (Cheong and Wu, 2014; Wang et al., 2013; Fan et al., 2011; Chen, 2010). Recognized the challenges, China has initiated several development programs to narrow regional gaps since the early 2000s. One of the major efforts is to boost agricultural productivity through technological change. To pursue sustainable agricultural productivity growth, China has continued to place high importance on agricultural technology research and development (R&D). China's government research funds in agriculture have been growing at an annual rate of more than 20% (NSBC). 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 programs since—including the large-scale western development, the rejuvenation of the northeastern region, and the boost-up of the central region. However, it is not clear whether the gap of agricultural productivity levels between China's most productive regions and those falling behind is narrowing down or in divergent paths. The answer to the above question is relevant to the future planning of China's agricultural policy.

The Neo-Classical Growth Theory implies a cross-region/country convergence where everybody benefits equally from the technological innovation without additional cost and eventually will grow toward the same rate in the steady state (Islam, 2003). Based on diminishing returns to capital assumptions, the Neo-classical growth theory (Solow,

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1956) predicts that an economy with a lower capital-labor ratio will have a 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 absolute convergence. Barro and Sala-i-Martin (1990) considered two types of convergence: one is a σ-convergence, which occurs when the dispersion of relative per capita income across economies/regions decrease over time; and the other is a β-convergence, which occurs when poor economies/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.

In the past researchers tended to investigate convergence issues from the perspective of per capita income—income convergence—or labor productivity (see Baumol, 1986; Baumol et al., 1994; Kumar and Russell, 2002, for example). However, income convergence (or labor productivity convergence) can be the joint outcome of capital deepening/input substitution and technological catch-up. In recent years, some researchers have paid attention to the process of technological change/catch-up based on total factor productivity (TFP) measures as TFP is the closest measure of technology (Jorgenson and Gollop, 1992; Jorgenson et al., 2014; Wolf, 2014). There are also distinct concepts and, therefore, different policy implications behind the convergence theory, such as whether the convergence will occur in terms of growth rate or in terms of level, or whether the convergence is conditional or unconditional.

This paper aims to address the following issues: (1) What is the recent performance of China’s regional agricultural productivity growth? (2) Are regional agricultural productivities converging in China? (3) What are the driving forces behind the convergence or divergence? (4) Can those who are falling behind catch up with the leading provinces in a short period? The existence of TFP convergence implies the improvement of disparity across regions. On the other hand, in the case of widening TFP gap, it will require the development of region-specific plans to stimulate the catch-up process in the farm sector.

In the literature, there are studies applying Data Envelopment Analysis (DEA)/Malmquist Index to address the TFP convergence issue based on technical efficiency estimates (see Li et al., 2008; Ma and Feng, 2013 for examples regarding China’s agriculture sector, and Nin et al., 2003; Ludena et al., 2007 for examples of other industries/countries). However, the convergence tests require measures of the level of productivity, not just the productivity growth rate many of those studies are therefore utilizing the inefficiency levels to evaluate the catch-up effects. One disadvantage of the Malmquist index approach is that the estimates of inefficiency level can vary when the sample regions change that affect the estimate of the frontier. Nin et al. (2003) point out that the DEA approach may result in inconsistent TFP measures when comparing with other methods. In addition, the causes of TFP spillover or catch-up effect could be different from efficiency catch-up. To avoid these issues, we adopt a superlative index number approach (Caves et al., 1982, CCD thereafter) to measure multilateral TFP estimates across China’s regions and over time in convergence tests. It may also avoid potential endogeneity issues when using econometric frontier approach (Phillips and Sul, 2009; Gong, 2018). Utilizing rolling revenue shares of individual commodities and cost shares of individual inputs as the weights the multilateral TFP estimates also capture the transitional behaviors of production at China’s provincial level. The paper contributes to the literature in three major ways: (1) this is the first convergence study that employs multilateral TFP panel data to conduct convergence tests for China’s agricultural sector; (2) this is the first China study that addresses convergence issues from the perspectives of both TFP levels and TFP growth rates in the aggregate farm sector, which is crucial as they have different policy implications; and (3) this study also fills the gap by comparing China's rate of convergence with those of the developed countries, such as the U.S., to test theoretical robustness.

The remainder of the article is organized as follows. Next section describes the methods of measuring multilateral TFP as well as σ and β convergences tests. We also describe data sources of variables used in the TFP measurement and convergence tests. Section 3 presents regional TFP estimates. Section 4 discusses econometric results obtained from convergence tests and their policy implications. Finally, in the last section, we summarize our main findings and address their policy implications in the concluding remarks.

2. Methods and data

2.1. Multilateral total factor productivity measurement

When conducting β convergence test, we need to employ a panel of relative TFP level estimates that allow the testing of the inverse relationship between initial TFP levels and TFP growth rates in subsequent periods. For this purpose, we apply a multilateral TFP panel dataset to conduct convergence tests for China’s regional agricultural productivities. Wang et al. (2013) applies a superlative index approach proposed by Caves et al. (1982, CCD thereafter) to construct multilateral outputs, inputs, and total factor productivity for twenty-five provinces/regions spanning the 1985–2007 period. We adopt the same approach[1] to extend the panel dataset through 2013 to provide more recent information. The details of the measurement of output and inputs can be found in Wang et al. (2013). In this section, our discussion focuses on the construction of transitive multilateral comparisons of output, inputs, and TFP.

TFP is a productivity measure that takes account of the use of all inputs to the production process. In a general form of growth accounting model, output (Y) can be expressed as a function of technology (A) and inputs (**X**):

$$Y = f(A, \mathbf{X}) \tag{1}$$

TFP is an estimate of the ratio of total real output (Y) over total real input (X) and a proxy of technology (A). There are various ways to measure TFP. In recent literature and official statistics, Törnquist-Theil (TT) index number[2] approach (an approximation of the Divisia index) has been widely used due to its superlative index number nature (Diewert, 1976). Using TT index, TFP changes for a specific province between two discrete points in time can be expressed as:

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

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 of producing output 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. Using average shares from two time points as the weighs TT index also accounts for any substantial changes in inputs or outputs over time.

[1] Wang et al. (2013) use detailed price and quantity information of individual commodities (including corn, cotton, peanut, rice, soybeans, and wheat, milk, pork, beef, mutton, chicken, eggs, and etc.) and inputs (including labor, intermediate goods—including seed, feed, fertilizer, pesticide, energy—land, and capital) to construct transitive estimates across twenty-five provinces/regions based on CCD approach. For some input measurement Wang et al. also follow methodologies proposed by Fan and Zhang (2002), Sun et al. (2007), and Sun and Ren (2008) in the study. Please see more detailed discussions in Wang et al. (2013).

[2] Tornquist -Theil index is consistent with a flexible translog functional form and therefore be seen as a superlative index number approach (Diewert, 1976).

To construct multilateral output, inputs, and TFP estimates, CCD proposed a methodology using superlative index numbers that under the CCD framework the translog multilateral output, input, and productivity indices are all transitive. We can, therefore, 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:

$$\ln\left(\frac{TFP_k}{TFP_l}\right) = \frac{1}{2}\sum_i (R_m^k + \bar{R}_m) * \ln\left(\frac{Y_m^k}{\tilde{Y}_m}\right) - \frac{1}{2}\sum_i (R_m^l + \bar{R}_m) * \ln\left(\frac{Y_m^l}{\tilde{Y}_m}\right) - \frac{1}{2}\sum_n (W_n^k + \overline{W}_n) * \ln\left(\frac{X_n^k}{\tilde{X}_n}\right) + \frac{1}{2}\sum_n (W_n^l + \overline{W}_n) * \ln\left(\frac{X_n^l}{\tilde{X}_n}\right) \tag{3}$$

where a bar indicates the arithmetic mean and a tilde indicates the geometric mean, R_m is the revenue share for output m, and 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. While there are more than twenty-five provincial level administrative divisions many of them do not have long time series of data or have relative smaller agricultural productions, such as Beijing, Tianjin, Shanghai, Hainan, and Tibet. Therefore, it is not uncommon that some regions are left out in China's agricultural study for data consistency. For example, Fan and Zhang (2002) covers twenty-five provinces, Huang and Rozelle (1995) covers twenty-three provinces, and Zhang and Carter (1997) covers twenty-two provinces. Following Wang et al. (2013) the multilateral output, inputs, and TFP indexes are extended to 2013 for China's twenty-five contiguous provinces[3] using Anhui province as the base province, and 1994 as the base year. Relative TFP levels for other provinces and other years are normalized to 1994 Anhui TFP level. The result is a panel with both temporal and spatial comparability.

2.2. Convergence hypothesis tests

We conduct three types of convergence test in this study. 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:

$$Var(lnTFP_t) = \varnothing_0 + \varnothing_1 t + \epsilon_t \tag{4}$$

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 $\varnothing_1 < 0$ (Lichtenberg, 1994; McCunn and Huffman, 2000). We conduct σ convergence tests using a TFP panel of full sample and TFP panels of seven subregions 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 the average rate of TFP growth over the interval T (Barro and Sala-i-Martin, 1991; McCunn and Huffman, 2000):

$$\left(\frac{1}{T}\right)\cdot ln\left(\frac{TFP_{i,t+T}}{TFP_{i,t}}\right) = \alpha_0 - \frac{(1-e^{-\beta T})}{T}\cdot \ln(TFP_{i,t}) + u_{it} \tag{5}$$

where i indexes the province, t indexes time, and 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 five years as the interval).[4] 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 $e^{-\beta T} < 1$, which 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 as absolute β convergence. To simplify the expression of Eq. (5), we replace the notation of average TFP growth rate over the interval T with $T\dot{F}P$, and substitute the coefficient of $\ln(TFP_{i,t})$ with $-\hat{b}$ so that

$$-\hat{b} = -\frac{(1-e^{-\beta T})}{T} \tag{6}$$

Eq. (5) can then be rewritten as:

$$T\dot{F}P_{it} = \alpha_0 - \hat{b}\cdot \ln(TFP_{it}) + u_{it} \tag{7}$$

Once the $\hat{b}$ coefficient is estimated we can then recover the β convergence coefficient from equation (6).

Third, we test for conditional β convergence. According to literature, the existing economy or region's specific conditions may also affect the rate of convergence or even result in divergence. 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 conducting a β convergence test with state-specific variables as control variables, such as the growth rates of K/L and M/L. 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 to test for the sensitivity and robustness of the β convergence coefficient and potential impacts of those control variables on regional TFP growth. We consider the following general form:

$$T\dot{F}P_{it} = \alpha_0 - \hat{b}\cdot \ln(TFP_{it}) + \sum_{j=1}^{\tau} \gamma_j \dot{Z}_{j,it} + u_{it} \tag{8}$$

where i indexes the province; t indexes time; $T\dot{F}P_{it}$ 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; and u_{it} is the disturbance term with zero mean and constant variance.

2.3. Data

The data for quantities, prices of individual outputs and inputs, aggregate revenue and expenditure are drawn from various sources, including China Agricultural Statistical Yearbooks (Ministry of Agriculture, 1985–2013a) National Agricultural Product Cost and Revenue Survey Data Books (Ministry of Agriculture, 1985–2013b), China Animal Husbandry Yearbooks (Ministry of Agriculture, 1990–2013), China Rural Statistical Yearbooks (NBSC, 1985–2013), and China Statistical Yearbooks (NBSC, 1985–2017) in various years.

[3] We follow Wang et al. (2013) using 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. Three province-level municipalities (Beijing, Tianjin, and Shanghai), one island province (Hainan) and one autonomous region (Tibet) are excluded as their output is small and data are not available for all years.

[4] Furthermore, China's central government set up 5-year development strategy, which is the guideline of the development in the next five years.

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)) 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 at least a high school education background. Since there is no R&D expenditure data at the provincial level, R&D variable is measured using the total number of staffs who work on research in agricultural research institutions as a proxy. China's agricultural R&D system is a public system, large in size but also decentralized (Huang and Rozelle, 2014; Babu et al., 2015). Each province has its regional agricultural research institutions (e.g., provincial agricultural university, the academy of agricultural sciences at provincial and prefectural levels). We assume that a greater pool of research staffs may deliver more research outputs that can contribute to the local agricultural productivity growth more directly and instantaneously. However, since the R&D staff data are only available for the period 1988–2005 at the provincial level, we conduct our convergence tests using a smaller sample with the shorter period when incorporating R&D variable in regression models. K/L and M/L are measured using the input estimates at the provincial level. Data sources include China Science and Technology Statistical Yearbooks, China Rural Statistical Yearbooks, and China Statistical Yearbooks in various years.

We summarize all descriptive statistics of control variables by region in Table 1. As we suspected the differences of those control variables within a region and across regions are quite large. For example, the average growth rates of the population who have at least a high school education background (Δln(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 the dispersion status in other regions. The means of the annual growth rates of the intermediate goods to labor ratio (Δln(M/L)) are somewhat close across regions ranging from 0.054 to 0.073, compared to that of the annual growth rate of capital to labor ratio (Δln(K/L)), which ranged from 0.04 to 0.52 over 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 variables are also high within each region implying that some provinces have smaller 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 that research staff was downsized for many provinces and periods of time. Still, the maximums of the average growth rates are still quite high in some provinces. We incorporate these variables in the convergence tests to control for the heterogeneity across provinces.

3. Patterns of China regional agricultural TFP growth

TFP growth rate estimates can vary upon measures. Chen et al. (2008) and Tong et al. (2012) find that China's agricultural productivity growth slowed in the late 1990s and then rebounded in later years based on the Malmquist index approach. Jin et al. (2010), however, shows TFP growth in 1995–2004 was higher than that in 1985–1994 based on a stochastic production frontier function approach. Wang et al. (2013), using the CCD approach, find average regional TFP growth rates dropped in the 2005–07 period and concern about a possible productivity slowdown. Gong (2018) find that China's agricultural TFP growth has cyclical fluctuations based on frontier approach. Using the same CCD approach as used in Wang et al. (2013) we find annual TFP growth rate estimates seem to rebound in the subsequent period (Fig. 1).

Since annual estimates of TFP growth rate can fluctuate from year to year due to transitory event (Fig. 1) we divide the whole period (1985–2013) into two sub-periods (each covering 14 years, 1985–1999 vs. 1999–2013) to evaluate the pattern of TFP growth between the two periods (Table 2, Fig. 2). According to Table 2 half of the provinces grew faster in the second period while the other half demonstrated slower growth after 1999. There is no statistical evidence showing overall slower growth in the second period, however (Table 2). On the other hand, a slower growth rate does not necessarily indicate a lower TFP level. Sometimes, a province with a lower TFP level in the beginning can grow faster than others, as so-called the catch-up effect. Between 1985 and 2013, the average annual growth rates of TFP range from Xinjiang's 1.92% to Shaanxi's 3.76%, which were higher than the average global agricultural productivity growth (Fuglie et al., 2012; USDA, 2017). They also exceeded the population growth rate in China (around 1.76%) (NSBC, 2017), indicating a substantial agricultural growth. Over the past three decades, the strong TFP growth in China farm sector has enabled China's agricultural output to continue to grow while using nearly 40% less of the labor force in agricultural production. However, TFP growth is unequal across regions, with some provinces growing faster than others. Overall, coastal provinces tend to have higher growth rates than most inner regions, ranging from 2.24% (Shandong) to 3.73% (Hebei) per year on average.

Table 3 presents the TFP rankings across provinces in both 1985 and 2013. According to the TFP estimates in 1985 Hunan, Guangdong, Jilin, Guangxi, and Sichuan are the top five provinces. In 2013, Zhejiang replaced Jilin in the top five list. On the other hand, while Shaanxi ranked 22nd in 1985, among the five lowest TFP provinces, it surpassed four provinces and ranked 18th in 2013. The heterogeneity of TFP growth by regions could be attributed to many factors, such as varied initial TFP levels and unequal resources distribution in R&D and human capital. We present the test results of the convergence hypothesis in the next section.

4. Econometric results of convergence tests

A few studies examine the hypothesis of TFP convergence issue using U.S. farm sector data (McCunn and Huffman, 2000; Ball et al., 2004, 2013 among others). McCunn and Huffman found evidence of "catching-up" (β-convergence) in state agricultural TFP but rejected the

Table 1
Descriptive statistics on individual control variables by region.
Source: Authors' calculations.

Region	Δln(Ed)		Δln(M/L)		Δln(K/L)		Δln(RD)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
East	0.040	0.025	0.073	0.059	0.044	0.056	−0.034	0.039
Middle	0.071	0.071	0.076	0.024	0.045	0.032	−0.036	0.028
Northeast	0.013	0.024	0.060	0.047	0.052	0.094	−0.039	0.040
Northwest	0.228	1.035	0.054	0.035	0.004	0.066	−0.031	0.023
North	0.027	0.022	0.075	0.046	0.030	0.042	−0.035	0.041
Southwest	0.074	0.096	0.065	0.030	0.039	0.049	−0.034	0.039
South	0.035	0.016	0.061	0.041	0.033	0.039	−0.028	0.029

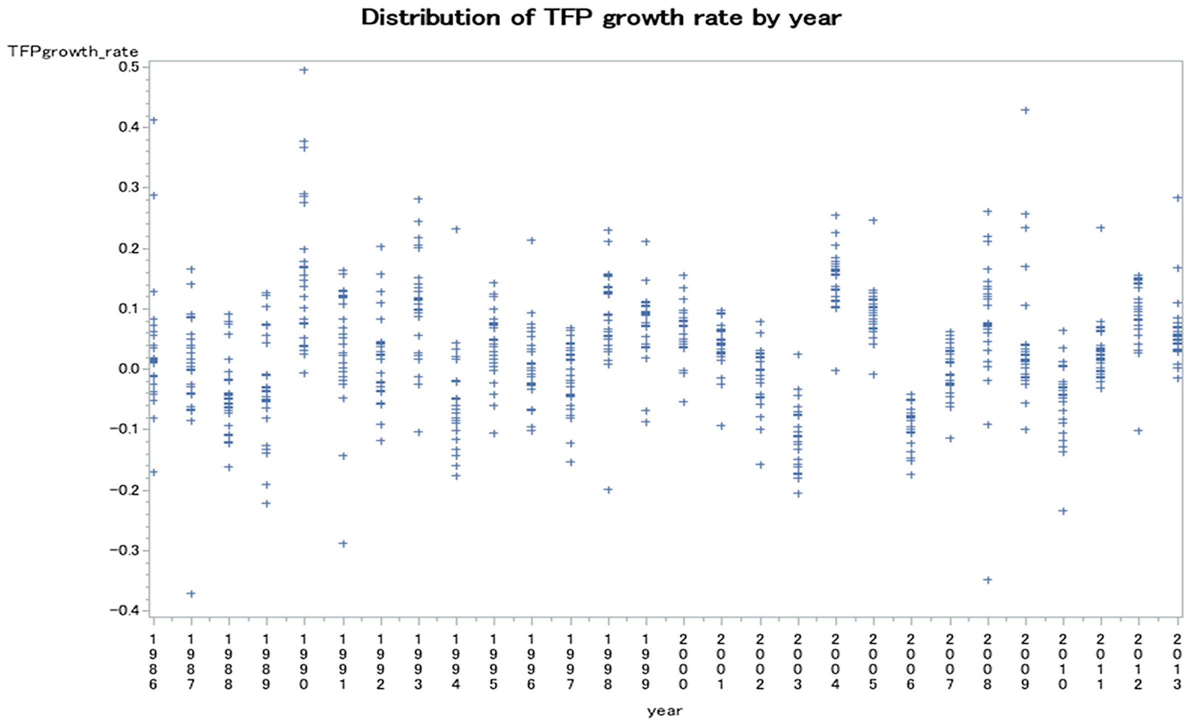

Fig. 1. Distribution of TFP growth rate.
Source: authors' calculations.

hypothesis of declining cross-sectional dispersion (σ-convergence). Ball et al. (2004, 2013) also find evidence of β-convergence after controlling for variables that capture regional differences. As to China's 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. However, as mentioned above, labor productivity can be affected by adding other inputs and not necessarily reflect the level of technology advancement. Using data envelopment analysis (DEA), Li et al. (2008) find evidence of σ- convergence in Chinese agricultural productivity for the 1980–2005 period. Ma and Feng (2013) find a convergence in China's agricultural efficiency. The limitation of the DEA approach, as mentioned above, does not allow for identifying the relative productivity levels across regions and over time, and therefore no β-convergence tests are conducted in those studies. We discuss results of convergence tests in the order of the σ convergence tests, the absolute β convergence test, and the conditional β convergence test to identify how China's regional agricultural productivities are converging, if any, and potential policy implications behind that.

4.1. σ Convergence test results

We first conduct stochastic convergence tests that are related to the unit root hypothesis (Bernard and Durlauf, 1995; Carlino and Mills, 1996). The stochastic convergence test bases on the 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, Dickey and Fuller, 1981) that evidence of a unit root indicates no convergence. Following this concept, we conduct unit root tests using ADF, Phillips-Perron (PP, Phillips and Perron, 1988), and Zivot-Andrews (Z-Andrews, Zivot and Andrews, 1992) tests, where Z-Andrews test allows for a structural break. We use a time series of annual cross-sectional variances of provincial TFP in the full sample, as well as subsamples clustered by geo-econ regions (Table 4). Results show that only the South region rejects the hypothesis of a unit root without trend, indicating a stochastic convergence in the South region. After considering intercept structural break (based on Z-Andrews test), Middle, North, and Northwest regions also demonstrate stochastic convergences.

We then conduct standard σ convergence tests for all twenty-five provinces and each geo-econ group by regressing annual cross-sectional variances of provincial TFP levels[5] with a time trend. We fit Eq. (4) with OLS estimations (Table 5). According to the results, the coefficient of the time trend is either positive or insignificant for all regions except for South region, indicating a σ convergence in the South regions as shown in the stochastic convergence tests. After considering a structural break, selected by the Z-Andrews tests, the time trend coefficient for the Northeast region has become negative and statistically significant. For East, North, Northwest, and Southwest regions it seems convergence only happened in their post-breakdate periods. In sum, there is no robust evidence showing an unconditional agricultural TFP convergence (σ convergence) across all regions except for the South region. However, the hypothesis of stochastic convergence holds for a few regions based on unit root test results, especially in recent years (as shown in the post-breakdate period).

4.2. β Convergence test results

We plot the initial TFP level vs. corresponding average annual TFP growth rate in the subsequent period for each of the twenty-five provinces in Fig. 3. It demonstrates that there are a few clusters with inverse relationships between initial TFP level and TFP growth rate. It seems that even β convergence exists they may not converge into the same TFP level. It is supportive evidence to the results of σ convergence test from the previous section that there is no overall σ convergence across all provinces, even they are within the same country border. Before investigating the hypotheses of absolute β convergence and

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

Table 2
Average annual TFP growth rates by province/region.
Source: Authors' calculations.

Region	Province	1985–2013	1985–1999 (A)	1999–2013 (B)
Northeast	Heilongjiang	2.18%	1.4%	3.0%
	Jilin	2.40%	3.4%	1.4%
	Liaoning*	2.69%	3.2%	2.2%
Region average		2.43%	2.7%	2.2%
North	Hebei*	3.73%	4.8%	2.7%
	Inner Mongolia	2.04%	2.2%	1.9%
	Shanxi	2.49%	0.7%	4.3%
Region average		2.75%	2.6%	2.9%
Middle	Henan	3.10%	3.6%	2.6%
	Hubei	3.31%	2.3%	4.3%
	Hunan	3.11%	2.6%	3.6%
Region average		3.17%	2.8%	3.5%
East	Anhui	1.97%	1.9%	2.0%
	Fujian*	3.29%	4.6%	2.0%
	Jiangsu*	2.97%	2.6%	3.4%
	Jiangxi	2.96%	3.0%	2.9%
	Shandong*	2.24%	2.7%	1.8%
	Zhejiang*	3.62%	2.9%	4.3%
Region average		2.84%	2.9%	3.0%
South	Guangdong*	3.19%	3.6%	2.7%
	Guanxi*	3.66%	3.5%	3.8%
Region average		3.42%	3.3%	3.2%
Southwest	Guizhou	2.04%	1.5%	2.6%
	Sichuan	3.44%	2.8%	4.0%
	Yunnan	3.91%	4.7%	3.2%
Region average		3.13%	3.0%	3.3%
Northwest	Gansu	2.24%	2.9%	1.6%
	Ningxia	3.76%	5.3%	2.2%
	Qinghai	3.30%	4.1%	2.5%
	Shaanxi	3.79%	3.4%	4.2%
	Xinjiang	1.92%	2.8%	1.0%
Region average		3.00%	3.4%	2.6%
National average		2.93%	3.06%	2.81%
Difference (A-B)			0.25%	
TTEST		DF = 349	t value = 0.34	

Note; "*" indicates coastal provinces.

conditional β convergence we first examine if each variable in Eqs. (5) and (8) are stationary to avoid spurious regression results in β convergence tests. 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) to examine if all variables in the regression models are stationary. According to the results (from both LL test and IPS test) (Table 6) we reject the unit root hypothesis for all variables except the growth rate of the 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 (Wang et al., 2011) and the increased capital investment that started from almost nothing before China's rural reform and its economy taking-off. 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 specifications (Model 4) to preserve its economic meaning and make comparisons with other model estimates for the robustness check of β convergence coefficients.

We conduct absolute β convergence tests by fitting Eq. (5) with a panel of full sample using fixed effect model estimation. The test result is presented in Table 7 as Model 1. The negative and significant sign of the initial TFP level confirms the existence of an absolute β convergence and a catch-up effect for those lagged behind. The estimated β convergence coefficient is 0.016. It is smaller than that estimated by McErlean and Wu based on China's agricultural labor productivity estimates. It is, however, similar to the rate of convergence (0.018) estimated by McCunn and Huffman based on the U.S. TFP data for the aggregate agricultural sector.

We then consider other control variables to capture heterogeneity across regions. We include an 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. While M/L growth rate has a positive impact on the TFP growth rate, K/L growth rate does not significantly affect TFP growth. We then drop the variable of K/L growth rate in Model 5 and add a time trend in the regression to capture an overall technical change effect and for comparison purpose. Results show that the rate of conditional β convergence in Model 5 is like the estimates in Model 4 and is more than two times of those calculated in models 1–3. The positive and significant impact of higher M/L ratio on TFP growth could also reflect a fact that excess labor in some inner regions resulted in a relatively lower M/L and inefficient use of labor force (Cai, 2018). For example, there is off-farm employment of rural labor force in developed regions (Li et al., 2013) while the off-farm employment rate is always relatively lower in western China.

In sum, the results of β convergence tests confirm the catch-up hypothesis that there is an inverse relationship between the rate of productivity growth and its initial level of TFP. However, unequally

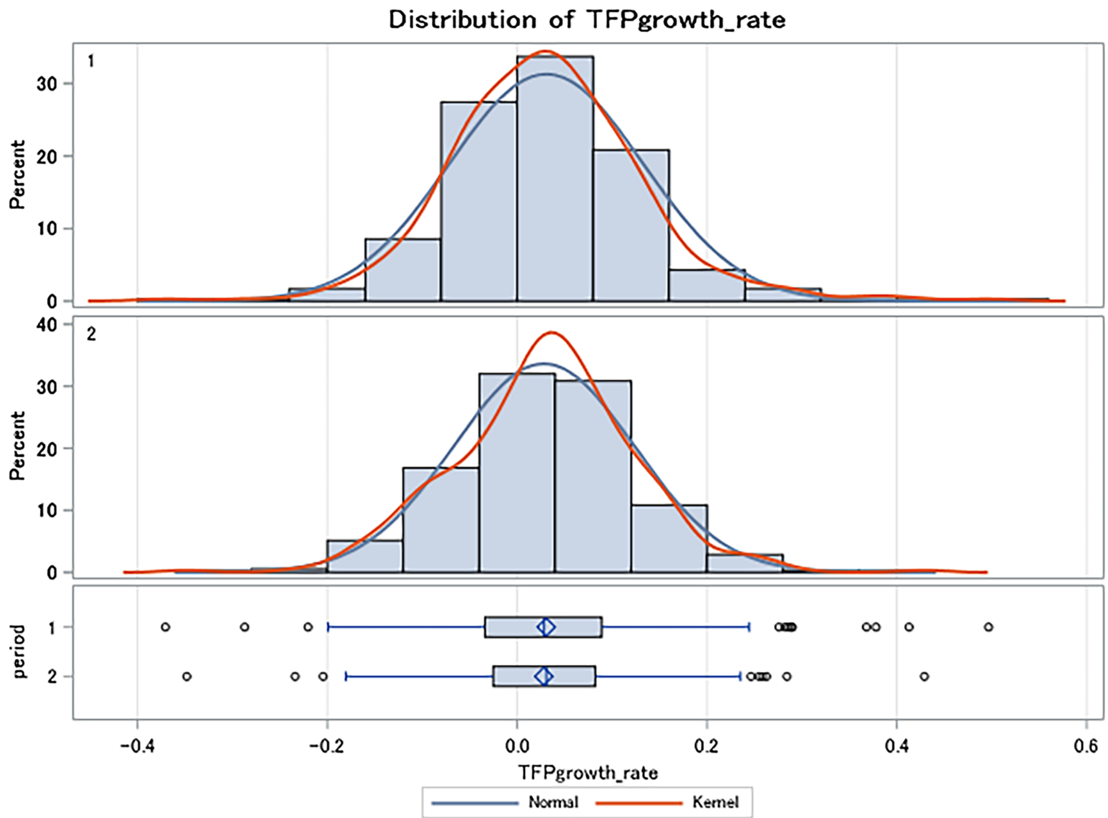

Fig. 2. Comparison of TFP growth rate distribution: 1985–1999 vs. 1999–2013.
Source: Authors' calculations.

Table 3
Changes of TFP rankings in China's farm sector.
Source: Authors' calculations.

Province	TFP rankings in 1985	TFP rankings in 2013	Changes[1]
Hunan	1	2	1
Guangdong	2	1	−1
Jilin	3	7	4
Guangxi	4	3	−1
Sichuan	5	5	0
Zhejiang	6	4	−2
Heilongjiang	7	19	12
Hubei	8	6	−2
Henan	9	9	0
Guizhou	10	16	6
Fujian	11	8	−3
Anhui	12	14	2
Jiangxi	13	17	4
Yunnan	14	11	−3
Shandong	15	10	−5
Liaoning	16	15	−1
Hebei	17	13	−4
Jiangsu	18	12	−6
Mongolia	19	20	1
Qinghai	20	22	2
Shanxi	21	21	0
Shaanxi	22	18	−4
Gansu	23	24	1
Xinjiang	24	23	−1
Ningxia	25	25	0

Note 1: the negative number indicates improvement in the TFP level rankings.

distributed R&D resources, different levels of human capital embodied in the labor force, and different levels of embodied technology through the use of agricultural chemicals and other intermediate goods can all affect the rate of convergence across regions. Our findings are

Table 4
Unit root test results.
Source: Authors' calculations.

Variables	ADF test statistics	Phillips-Perron test	Zivot-Andrews test	break
Var(lnTFP_all)	-3.945^{**a}	-4.089^{**a}	-4.267^{*a}	1989
Var(lnTFP_East)	-3.411^{*a}	-3.484^{*a}	-2.614^{a}	1994
Var(lnTFP_Middle)	-3.049^{a}	-2.931^{a}	-7.78^{***}	2002
Var(lnTFP_North)	-1.717^{a}	-1.734^{a}	-7.649^{***}	2009
Var(lnTFP_Northeast)	-1.895^{a}	-1.993^{a}	-4.441	1998
Var(lnTFP_Northwest)	-3.566^{*a}	-3.791^{***}	-5.273^{**}	1998
Var(lnTFP_South)	-3.568^{**}	-3.484^{**}	-6.402^{***}	2008
Var(lnTFP_Southwest)	-3.693^{**a}	-3.642^{**a}	-4.129^{*a}	1991

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.

consistent with those for the developed countries (see McCunn and Huffman, for example).

In a recent study Wei et al. (2017) warn about the sustainability of China's aggregate economic growth and urge the necessity of innovation and productivity increase for future economic development to avoid the middle-income trap[6] (Ma, 2016; Gill and Kharas, 2017). On the other hand, this middle-income trap hypothesis may also apply to regional development. While we find that TFP growth rates tend to be higher for those starting from relatively low TFP levels, showing some

[6] The middle-income trap hypothesis asserts that without exceptional innovation the middle-income countries may hardly catch up with the high-income countries even with a speedy growth in the early development stage (World Bank, 2017).

Table 5
σ convergence test results.
Source: Authors' calculations.

	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	breakdate
All regions	0.0050	6.72***	0.612	0.0189	3.22***	−0.0128	−2.38**	0.670	1989^{a}
East	0.0027	6.66***	0.608	0.0034	6.66***	−0.0006	2.82**	0.595	1994^{a}
Middle	0.0021	2.21**	0.122	−0.0016	−1.05	0.0732	2.73**	0.292	2002^{b}
North	0.0064	4.33***	0.388	0.0125	16.14***	−0.2063	−12.06***	0.904	2009^{b}
Northeast	0.0027	3.46***	0.282	−0.0026	−2.74**	0.1037	6.37***	0.709	1998^{b}
Northwest	−0.0003	−0.31	0.033	0.0052	2.81***	−0.1075	−3.48***	0.268	1998^{b}
South	−0.0052	−3.14***	0.241	−0.0012	−0.59	−0.1156	−2.69**	0.384	2008^{b}
Southwest	0.0052	5.20***	0.482	0.0203	3.1	−0.0136	−2.33**	0.555	1991^{a}

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.

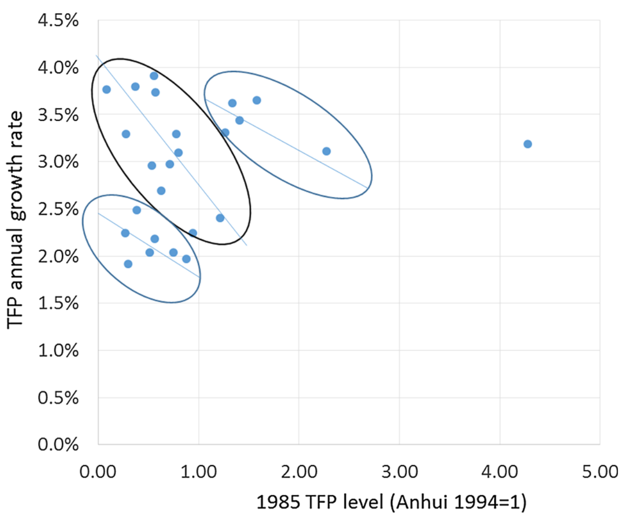

Fig. 3. Initial TFP vs. annual TFP growth rate in China's farm sector (1985–2013).
Source: Authors' calculations.

Table 6
Panel unit root test results.
Source: Authors' calculations.

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	−5.5000^{***a}	−3.5540^{***a}
(K/L) growth rate	0.6315^{a}	4.5207^{a}
(M/L) growth rate	−5.2574***	−3.5396***

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.

degree of the catch-up effect, the high TFP growth may not persist if other resources are not catching up enough. When controlling for regional heterogeneity using provincial level R&D, education, and intermediate goods density (per unit of labor) variables, we find that the convergence rate can be boosted if resources are distributed more equally. It could shed light on regional development and agricultural R&D.

5. Concluding remarks and policy implications

This study shows that China's agricultural TFP has grown at nearly 3% since the middle 1980s, which were higher than most of the developed and developing countries (Fuglie et al., 2012) during the same period. This high growth of agricultural productivity is consistent with the observation that China has developed strong public agricultural R&D program and extension system, both are the largest in the world in terms of staff (Huang and Rozelle, 2014). Government investment in agricultural R&D has also increased significantly and exceeded RMB26 billion (about USD 4.2 billion) in 2015 (Huang and Rozelle, 2018). Over the past decade, an increasing number of enterprises have also engaged in agricultural R&D activities.

However, China is a big country with a vast territory and large variation in economic development. Interregional economic disparity is becoming a severe problem in this transforming economy with fast economic growth in the last four decades. While the estimated average TFP for China has been strong, it varied significantly among provinces during 1985–2013, ranging from 1.92% to 3.91% per annum.

We employ multilateral TFP estimates to investigate hypotheses of productivity σ convergence and β convergence for China's farm sector, using a panel of twenty-five provinces, spanning the 1985–2013 period. Econometric results show that there is no evidence of an overall unconditional TFP convergence (σ convergence) across all provinces and within each region, except for the South region. When considering a structural break in the intercept Middle, North, and Northwest regions demonstrate stochastic convergence in their post-break periods, respectively. However, those test results do not inform the causes behind the convergence/divergence. 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 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 region-specific variables the rate of β convergence is accelerated, ranging from 0.016 to 0.038 across various models. Regression results also show that a higher growth rate of education, R&D, or relative intermediate goods/labor ratio—can boost TFP growth. These findings imply that unequally allocated resources of agricultural research and human capital can hinder the rate of convergence.

The results of this study have several important policy implications. China's experience shows the important role of agricultural productivity growth for the nation's food security. The estimated agricultural TFP growth (2.93% per annum) contributed nearly 60% of China's agricultural output growth (4.8%) during 1985–2013 (NSBC, 2018), which explains how China has been able to largely meet its growth demand for nearly 20% of the world's population with only about 5% of the world's fresh water and 8% of the world's arable land.

Table 7
β convergence test results.
Source: Authors' calculations.

	Model 1		Model 2		Model 3		Model 4		Model 5	
Dependent variable: five year overlapping TFP average growth rate	coefficients	t-statistics	coefficients	t-statistics	coefficients	t-statistics	coefficients	t-statistics	coefficients	t-statistics
Constant	0.0228	13.18***	0.0286	15.97***	0.0161	5.91***	−0.0747	−8.42***	−0.0705	−8.29***
lnTFP	−0.0762	−9.89***	−0.0864	−11.47***	−0.0836	−11.67***	−0.1756	−16.70***	−0.1733	−16.58***
Hi-Ed growth rate			0.0200	7.41***	0.0177	6.86***	0.0178	8.07***	0.0176	7.99***
RD staffs growth rate			0.2140	5.69***	0.2272	6.36***	0.1644	5.11***	0.1516	4.84***
(M/L) growth rate					0.1977	5.88***	0.1704	5.99***	0.1541	5.32***
(K/L) growth rate							−0.0452	−1.63		
Time trend							0.0053	10.49***	0.0050	10.58***
calculated β	0.0159		0.0181		0.0175		0.0386		0.0381	
F statistics		71.77***		76.79***		72.75***		86.27***		102.41***

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.

However, our study also shows that the regional disparities on agricultural productivity and its growth are large. Although there is evidence of catch-up effect of agricultural TFP among provinces, large and significant regional productivity convergence has not occurred. Given the important role of agricultural productivity growth in agricultural output growth in China, the development of region-specific plans to stimulate the catch-up process of agricultural productivity is essential. For example, despite recent government's initiatives on balancing regional development, empirical studies have shown that there are still large regional gaps in rural education and other public good provisions (Wang et al., 2018).

Although the government has substantially increased its agricultural R&D in the past two decades in China, there is an observation of an increasing concentration of agricultural R&D in the coastal and more developed regions over time. Without increased research in support of agricultural technology and innovation, agricultural TFP in less developed regions may fall further behind in the future. Besides, less productive provinces with excess on-farm labor can be left far behind if the condition remains unchanged. Continue to provide more off-farm employment opportunities to rural labor in less developed regions may be one way to improve their agricultural productivity. In 2017, China initiated a rural revitalization strategy aimed at largely modernizing agriculture and the rural economy by 2035, and fully modernizing them by 2050. While this initiative is impressive, a rural modernization process may require explicit attention devoted to research and off-farm labor opportunities to be fully effective.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2019.05.010.

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