China Economic Review 60 (2020) 101423

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Agricultural productivity convergence in China

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ARTICLE INFO

Keywords:
Agricultural convergence
Total factor productivity
Stochastic frontier analysis
Reform and opening up in China
County-level and commodity-level data

JEL codes:
D24
O47
Q10
O13

ABSTRACT

This article investigates the progress and prospects of agricultural productivity catch-up in China since the rural reform. A model averaging method is employed to jointly consider four productivity estimates, which can better capture the province-specific and non-linear trend of productivity that was estimated with bias in previous literature. This article then utilizes three convergence tests to evaluate whether convergence has occurred and explores channels through which agricultural convergence can be achieved or accelerated. Using three panels at the province, county and commodity levels, this article concludes that agriculture is not on the right track to catch-up, since 23 out of 28 provinces and 19 out of 23 farm commodities fail to converge. However, the productivity gap may diminish in the future if the irrigation, education, public expenditure and structural transformation for lagging provinces can be improved.

1. Introduction

The initiative behind China's economic reform in the late 1970s began in rural areas and the agricultural sector. The miraculous growth in agricultural outputs, which increased from 0.14 trillion CNY in 1978 to 11.5 trillion CNY in 2017, has played a fundamental role in poverty reduction and food security. More importantly, the tremendous growth in total factor productivity (TFP) has decreased the demand for agricultural inputs, especially in terms of labor force, which leads to rural–urban migration. An abundant food and workforce guarantees industrialization and urbanization, which has further boosted the rapid growth in non-agricultural sectors since the 1990s. Therefore, agricultural growth is a key condition, or even a precondition, for growth of the entire economy (Ruttan, 2002). To summarize, China's agricultural productivity growth has been at the forefront of sustainable development and is the foundation of the country's economic growth.

Before the rural reforms, agricultural growth was mainly driven by growth in inputs, especially the expansion in arable land and labor force. Since the late 1970s, however, agricultural TFP growth, given the fixity of cultivated land and the shrinking agricultural population, had become the major driver of agricultural growth. As a result, productivity growth in China's agricultural sector has been the subject of intense research by many economists (e.g., Lin (1992), Brümmer, Glauben, and Lu (2006), Jin, Ma, Huang, Hu, and Rozelle (2010), Yu (2012), and Gong (2018a)). Ruttan (2002) states that there are three stages in agricultural productivity studies: efforts directed toward the measurement of partial factor productivity and then total factor productivity in the first two stages, followed by tests for agricultural productivity convergence, which is the core of the third stage. In China's agricultural

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https://doi.org/10.1016/j.chieco.2020.101423
Received 6 November 2018; Received in revised form 5 November 2019; Accepted 6 February 2020
Available online 07 February 2020
1043-951X/

analyses, many scholars studied partial factor productivity (e.g., Lin (1994), Huang and Rozelle (1996), Jin and Deininger (2009)) and total factor productivity (e.g., Mcmillan, Whalley, and Zhu (1989), Fleisher and Liu (1992), Fan and Zhang (2002), and Gong (2018c)).

In the third and current stage, convergence tests for agricultural productivity are of great importance. After 40 years of rapid growth, many believe the gap between coastal area and inland area has increased. Convergence tests indicate whether laggards are catching up to leaders (Henderson & Russell, 2005) and shed light on the conditions under which lagging regions enjoy an "advantage of backwardness" to help design development policies (Inklaar & Diewert, 2016). Many scholars (e.g., Jin et al. (2010), Ma and Feng (2013)) emphasize the importance of such agricultural catch-up to reduce disparity and boost the economy in China. However, less attention has been given to examining the evidence and rate of agricultural productivity convergence in China. Wu (2000) and Peng (2005) both use convergence tests after estimating productivity to check the catch-up among China's regional economies, but they focus on the whole economy, rather than solely the agricultural sector. McErlean and Wu (2003) test agricultural convergence in China, but they study labor productivity, rather than the more comprehensive total factor productivity. Ma and Feng (2013) use data envelopment analysis (DEA) to estimate province-level productivity and technical efficiency and then test China's agricultural convergence over the period of 1994–2008. Wang, Huang, Wang, and Tuan (2019) use σ-convergence tesst and β-convergence test on multilateral TFP estimates to investigate China's agricultural convergence during the period of 1985–2013.

There are three reasons that motivate us to reinvestigate the progress, sources, and prospects of China's agricultural convergence. First, DEA cannot distinguish productivity from measurement error and white noise (see details in Section 2.2), which motivates this article to re-evaluate China's agricultural convergence using other appropriate methods. Moreover, technology spillovers and catch-ups occur more easily within the same province or for the same commodity, which motivates us to investigate provincial convergence and commodity-specific convergence. Such an investigation can better describe the progress of convergence at a more disaggregated level and can also reveal which provinces and commodities are the major sources of China's agricultural convergence. The third motivation is that understanding how to enhance agricultural convergence in the future is important, but is less commonly studied.

This article aims to calculate accurate agricultural productivity and then investigate whether agricultural convergence has occurred during the past 40 years of reform in China. A jackknife model averaging method is utilized to jointly consider four stochastic frontier models when estimating agricultural productivity. This article then uses two convergence tests (σ-convergence and unconditional β-convergence) to determine whether agricultural productivity catch-up has occurred using three panels at the province, county, and commodity levels. Finally, a conditional β-convergence test is adopted to investigate methods to enhance convergence in the future.

This article makes three central contributions to the literature of agricultural productivity and convergence. First, four different estimators are jointly considered to better capture the individual-specific and non-linear trend of productivity growth using a model averaging method. Second, to our best knowledge, it is the first study that disaggregates China's provincial data on agriculture to both the county level and commodity level so that provincial convergence and product-specific convergence can also be tested, which further investigates the sources of China's agriculture convergence. Third, it not only tests whether agricultural convergence has occurred in China, but also explores potential channels through which convergence can be achieved or accelerated.

Using a balanced panel of 31 provinces from 1978 to 2015, this paper finds that agricultural convergence has not occurred after 40 years of reform, indicating that the gaps between the leading and lagging provinces failed to be diminished. Furthermore, 23 out of 28 provinces and 19 out of 23 farm commodities failed to converge, according to convergence tests on a county-level panel for 1861 counties and commodity-level panels for 23 farm commodities. In order to return to the right track toward convergence, broader irrigation systems, higher education in rural areas, greater agricultural public expenditure, and faster structural transformation are needed for those that lag behind.

The remainder of the article is organized as follows. Section 2 reviews the literature, Section 3 describes the methodology, Section 4 introduces the data used, Section 5 presents and discusses the empirical results, and Section 6 ends with concluding remarks.

2. Literature review

This section first introduces existing studies on China's agricultural productivity and convergence, and reviews the methods used in this line of research.

2.1. China's agricultural productivity and convergence studies

The implementation of rural reforms has overwhelmingly reshaped China's agriculture since 1978, which has drawn significant attention to agricultural productivity analysis to evaluate the impact of reforms. Due to different waves of institutional reforms and market deregulations, agricultural TFP growth rate has changed over time. Gong (2018a) divides 40 years of China's rural reforms into six periods and finds very different TFP trends across periods. In the first period (1978–1984), rapid growth in productivity has been discovered and agreed on by many scholars (e.g., Mcmillan et al. (1989), Wen (1993), Fan, Zhang, Dong, Song, and Zhang (2002), Fan, Zhang, and Zhang (2004)). Decollectivization and decentralization in this period, especially the household responsibility system (HRS), turned to economic incentives to spur growth (Ahmad, 2018; Lin, 1992; Oi, 1999; Zheng, Gu, & Zhu, 2019). In the second period (1985–1989), however, agricultural slowdown has been witnessed (Carter & Estrin, 2001) due to the government's failure in market liberalization (Huang, 1998; Sicular, 1995) and the exhaustion of the transitory positive effect following the first period (Fan, 1991; Fan et al., 2004; Lin, 1992; Mcmillan et al., 1989). In the third period (1990–1993), China introduced some adjustment policies to substitute the centrally planned system in favor of more market oriented solutions (Brümmer et al., 2006), which rebounded productivity growth (De Brauw, Huang, & Rozelle, 2004; Wu, Walker, Devadoss, & Lu, 2001). Different from the first three periods, the TFP trends since the late 1990s have been controversial. Some scholars believe that productivity stagnated in the late 1990s, but gained its momentum again in the 2000s (Chen, 2006b; Chen, Ming-Miin, Chang, & Hsu, 2008; Tong, Fulginiti, & Sesmero, 2009; Zhou & Zhang, 2013), while others find that productivity growth continued to increase in the late 1990s and then suffered from a slowdown in the 2000s (Dekle & Vandenbroucke, 2010; Pratt, Yu, & Fan, 2008; Wang, Tuan, Gale, Somwaru, & Hansen, 2013). To summarize, China's agricultural TFP trend is changing and controversial across reform periods. Therefore, reliable convergence analysis to estimate and forecast the long-term TFP trend is of great significance.

Using province-level panel data, Ma and Feng (2013) adopt a DEA method and find some evidence of agricultural convergence in China from 1994 to 2008. However, Ma and Feng (2013) point out that the use of province-level data may cause bias in regression estimation. One way to solve the problem is to disaggregate agriculture to various farm commodities. Jin, Huang, Hu, and Rozelle (2002) find an increasing TFP trend for three crops—rice, wheat, and maize—from 1979 to 1995, but the TFP growth of rice was slower than the ones for wheat and maize. Jin et al. (2010) also point out that horticulture and livestock production has boomed, whereas other crops have stagnated or even fallen, which makes commodity-specific analysis necessary. The second approach to disaggregation is to use county-level or farm-level data instead of province-level data. Carter and Estrin (2001), Brümmer et al. (2006), Chen, Huffman, and Rozelle (2009), and Liu, Zhang, He, and Jing (2015) use city-level and farm-level data for several provinces to estimate agricultural productivity and efficiency, which is not nationally representative. Monchuk, Chen, and Bonaparte (2010) use county-level cross-sectional data of 2028 counties, which fails to measure long-term trends. As Ma and Feng (2013) concluded, the availability of panel data at the county or farm levels remains incomplete. Therefore, most of the agricultural productivity analyses still use provincial data (Kalirajan, Obwona, & Zhao, 1996; Lambert & Parker, 1998; Tian & Wan, 2000).

Convergence is easier to achieve within the same province and within the same commodity due to faster technology spillovers and more similar characteristics. However, existing studies fail to investigate which provinces and commodities are the main sources of the overall convergence. This research gap motivates us to test within-province and within-commodity convergence.

2.2. Agricultural productivity and convergence methods

The frontier methods, including stochastic frontier analysis (SFA) and data envelopment analysis (DEA), are the most popular statistical tools in the line of productivity analysis (Coelli & Rao, 2005; Ruttan, 2002). For example, Wu (2011) surveys 74 articles from the 1990s onwards that estimated TFP in China, where SFA has been used 22 times (e.g., Wu (1995), Carter and Estrin (2001), and Brümmer et al. (2006)) and DEA has been used 15 times (e.g., Mao and Koo (1997), and Liu et al. (2015)). Many studies (e.g., Suhariyanto and Thirtle (2001), Coelli and Rao (2005), and Rezitis (2010)) have adopted the DEA method to estimate agricultural productivity and then perform convergence tests, as in Ma and Feng (2013). However, some scholars point out that DEA-based productivity measures often provide anomalous results (Headey, Alauddin, & Rao, 2010). Nin, Arndt, and Preckel (2003) claim that DEA-derived TFPs usually draw quite inconsistent conclusions as compared with those from other measures of agricultural development, since DEA cannot distinguish productivity from measurement error and white noise. In the agricultural sector, however, measurement error and white noise always exist. On the one hand, agricultural inputs and outputs data may be deeply flawed in China and in many other countries (Headey et al., 2010).[1] On the other hand, agriculture is sensitive and heavily affected by environmental shocks, such as rainfall and pests, which are difficult to control in a deterministic production function. Neither of the two issues can be fully addressed by DEA methods.

Stochastic frontier analysis, on the other hand, is able to deal with both issues and rule them out because it is a stochastic model. Comparing the SFA and DEA methods on FAO data, Coelli, Rungasuriyawiboon, and Rao (2004) and Headey et al. (2010) both point out that SFA estimations are significantly more stable and plausible than those derived by DEA. However, the current utilization of SFA to test agricultural productivity convergence is not perfect. Most of the existing studies (e.g., Kumbhakar and Wang (2005), Deliktas and Balcilar (2005), and Headey et al. (2010)) adopt the Error Components Frontier (ECF) method proposed by Battese and Coelli (1992). However, ECF assumes a similar monotonic trend of technical efficiency for various regions, which is a strong assumption and fails to capture region-specific and non-monotonic fluctuation over time (Gong, 2018b). In recent years, many new SFA models (e.g., Greene (2005), Greene (2008), Wang and Ho (2010), Kumbhakar and Tsionas (2011), Kneip, Sickles, and Song (2012), and Kumbhakar, Lien, and Hardaker (2014)) are developed to allow more flexible trend of efficiencies. But these new methodologies have not been widely used in agricultural productivity and convergence analyses.

Once TFPs are derived, this article uses three convergence tests that are frequently used in literature (e.g., Cameron, Proudman, and Redding (2005), Madsen (2007), and Inklaar and Diewert (2016)). It is worth noting that the key methodology problem that motivates this article is to look for appropriate methods to more precisely derive agricultural productivity, which is the foundation of a convincing convergence analysis.

3. Model

This section first introduces four stochastic frontier models. Model averaging method is then employed so that all these four

[1] For example, provincial machinery input is measured by total power of agricultural machines. However, a 400-hp combine harvester is not equal to ten 40-hp tractors. Moreover, some poor regions may not have enough capacity for statistical collection. This is not only a problem in China, but all over the world. Even Food and Agriculture Organization of the United Nations (FAO) agricultural data is always criticized by measure error.

models can be jointly used to estimate productivity. Convergence tests are established to evaluate whether convergence has occurred. Finally, some endogeneity issues and robustness checks are also discussed.

3.1. Basic stochastic frontier analysis

Productivity is an important measure of economic performance (Sheng & Song, 2013; Wang, Yamauchi, & Huang, 2016; Zhang, Wang, Glauben, & Brümmer, 2011). Stochastic Frontier Analysis (SFA) can estimate the production frontier, which represents the highest attainable TFP under current technology (Gong & Sickles, 2020). This method also calculates technical inefficiency, which accounts for the productivity gap of each unit compared to the most productive one (with the highest TFP), and therefore computes the TFP for each unit. The SFA model was initially proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977), and has been applied by many scholars (e.g., Xiang and Huang (2018), Mourao (2018), Chiu, Lin, and Yang (2019), and Gong (2019)).

Following Schmidt and Sickles (1984), this article establishes a stochastic frontier model for China's agricultural sector in the form

$$y_{it} = \alpha_t + \beta_1 land_{it} + \beta_2 labor_{it} + \beta_3 machine_{it} + \beta_4 fertilizer_{it} - u_{it} + \nu_{it} \tag{1}$$

where y_{it} accounts for agricultural output, $land_{it}$ measures land input, $labor_{it}$ measures labor input, $machine_{it}$ measures machinery input, and $fertilizer_{it}$ measures fertilizer input. All of these agricultural input and output values are for province i at time t and in logarithms. α_t represents the highest attainable TFP at time t and u_{it} is a non-negative variable that measures the agricultural productivity gap for province i at time t to the "best practice" productivity α_t. As a result, $\alpha_{it} = \alpha_t - u_{it}$ is the agricultural TFP for province i at time t. ν_{it} is the disturbance, which is similar to the measurement in Coelli, Rao, O'Donnell, and Battese (2005), Sickles and Zelenyuk (2019), and Gong (2020).

The production function may suffer from simultaneity bias as productivity levels are known to producers when they decide their input utilization but unobservable to economists (Gong, 2017). This endogeneity problem may lead to biased estimates of the production function and inaccurate TFP levels. Amsler, Prokhorov, and Schmidt (2016) establishes a control function method to test the endogeneity of each input in the stochastic frontier model using t-tests for the significance of the reduced form residuals.

3.2. Four estimators of SFA

In the last three decades, many scholars have developed different SFA methods to estimate TFP (α_{it}) in Eq. (1). This article introduces four estimators under different assumptions.

3.2.1. Fixed effects or random effects estimator

When productivity and technical efficiency are time-invariant for each province ($\alpha_{it} = \alpha_i$), then fixed effects (FIX) or random effects (RND) can be employed to estimate the stochastic frontier model (Schmidt & Sickles, 1984). This article uses the Hausman-Wu test to choose between FIX and RND estimators. However, if productivity and technical efficiency are time-variant, neither of the two methods can derive accurate results.

3.2.2. Error components frontier estimator

When technical efficiency is time-variant but follows a simple linear trend for each province, the Error Components Frontier (ECF) approach proposed by Battese and Coelli (1992) is the right model to use. ECF assumes that $u_{it} = \exp(-\eta(t - T)) \cdot u_i$, where $u_i \sim N^+(\mu, {\sigma_\mu}^2)$ follows a truncated normal distribution and solves the stochastic frontier model using Maximum Likelihood Estimation (MLE). ECF also assumes that the direction of efficiency changes remains the same for all provinces over the whole period due to the fixed η. Furthermore, the growth rate in technical efficiency for the same province is assumed to be fixed over time.

3.2.3. Cornwell-schmidt-sickles estimator

Cornwell, Schmidt, and Sickles (1990) proposes the Cornwell-Schmidt-Sickles (CSS) model, which is different from the ECF estimator. CSS model relaxes the fixed direction and linear trend assumption so that TFP can follow a nonlinear trend. More specifically, CSS assumes that the productivity has a quadratic time-varying formation $\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2$, where productivity is a quadratic function of time so that the non-linear trend over time can be modeled and the province-specific parameters $\theta_{i1} - \theta_{i3}$ so that the differences across provinces can be considered. Finally, Generalized Least Squares (GLS) estimation helps to derive the result of the CSS model.

3.2.4. Kneip-sickles-song estimator

Although it allows a non-linear trend TFP and is more flexible than ECF, CSS estimator still requires an assumption of the quadratic functional form. Kneip et al. (2012) established a semi-parametric model, known as the Kneip-Sickles-Song (KSS) model, which assumes that province-level efficiencies are influenced by a set of time-varying factors. In the KSS model, technical efficiency is modeled by $u_{it} = \sum_{r=1}^{L} \theta_{ir} g_r(t)$, where $g_1(t), \ldots, g_L(t)$ are the basis functions, and $\theta_{i1}, \ldots, \theta_{iL}$ are the corresponding province-specific parameters. As a result, KSS relaxes the assumption of functional form and is more flexible than CSS.

Table 1
Introduction of the four estimators.

Model	Source	Equation	Assumption on productivity trend
FIX/RND	Schmidt and Sickles (1984)	$\alpha_{it} = \alpha_i$	Time-invariant
ECF	Battese and Coelli (1992)	$\alpha_{it} = \alpha_t - \exp(-\eta(t-T)) \cdot u_i$	Linear Trend
CSS	Cornwell et al. (1990)	$\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2$	Quadratic Trend
KSS	Kneip et al. (2012)	$\alpha_{it} = \alpha_t - \sum_{r=1}^{L} \theta_{ir} g_r(t)$	Flexible

3.3. Choosing the best estimator

Deciding which the aforementioned four estimators is best depends on the true data generating process (DGP). Table 1 explains the best estimator under different circumstances. If the provincial TFPs are time-invariant, the FIX or RND estimator is the ideal method to utilize. If all provincial technical efficiencies move in the same direction and each of them follows a linear trend, the ECF estimator is the best to model the production process. If the agricultural productivity of various provinces moves in different directions and the changes approximate to a quadratic trend for most provinces, CSS should be selected. If the changes in technical efficiency follow a more complex trend than quadratic, KSS can be considered to estimate the stochastic frontier model. It is worth noting that the semi-parametric KSS model is the most general model among the four estimators and requires the least assumptions, but it may encounter computational challenges. To summarize, the optimal choice of estimator heavily depends on the true DGP.

However, the next puzzle is that the true DGP remains unobserved. More importantly, the TFP growth of some provinces may follow a certain trend, whereas the TFP growth of other provinces may follow a different trend. Even for the same province, the trend may vary over time, as a fundamental transition has occurred during the 40 years of rural reform in China. As a result, none of the four methods alone is sufficient to explain the agricultural productivity trend for all provinces in China. Therefore, a model selection method that chooses only one of the four estimators may not be a good fit, as multiple candidate models may partially reflect the underlying DGP.

In order to jointly use various candidate models, this article assigns a weight to each candidate model based on its ability to explain the sample data, which is known as the model averaging method. More specifically, a jackknife model averaging (JMA) method proposed by Hansen and Racine (2012) is adopted. JMA follows a "leave one out" cross-validation criterion to assign weights to various models so that the weighted average model is asymptotically optimal and approaches the minimum expected square errors when the sample size approaches infinity. This article denotes the jackknife estimates as $\hat{y}^j = (\hat{y}_1^j, ..., \hat{y}_n^j)\ \forall\ j = 1, 2, 3, 4$, where $\hat{y}_i^j$ accounts for the fitted value of province i's agricultural output using the j-th estimator and the subsample without the observations of province i. The first to the fourth estimators are FIX/RND, ECF, CSS, and KSS, respectively. The jackknife weights $w^* = (w_1^*, \ldots, w_4^*)$ are derived by minimizing the cross-validation criterion $w^* = \underset{w^*=(w_1^*,\ldots,w_4^*)}{\operatorname{argmin}} CV_n(w) = \frac{1}{n}\hat{e}(w)'\hat{e}(w)$, where $\hat{e}(w) = y - \sum_{j=1}^{4} w_j \hat{y}^j$ and $\sum_{j=1}^{4} w_j = 1$. This article then creates the JMA estimator by calculating the weighted average of the four candidate models, which is based on the jackknife weight w^* and has the form

$$y_{it} = \sum_{j=1}^{4} w_j^* f_j(x_{it}) \tag{2}$$

where $f_j(x_{it})$ is the j-th estimator of the stochastic frontier model in Eq. (1). The JMA-based TFP is the jackknife-weighted averages of the TFPs estimated by the four models:

$$TFP_{it} = \exp(\hat{\alpha}_{it}) = \exp\left(\sum_{j=1}^{4} w_j^* \hat{\alpha}_{it}^j\right), \tag{3}$$

where $\hat{\alpha}_{it}^j$ is the agricultural TFP estimated by the j-th model.

3.4. Convergence tests

This article adopts three convergence tests that are frequently used in literature (e.g., Cameron et al. (2005), Madsen (2007), and Inklaar and Diewert (2016)). The first method is the σ-convergence, which has been widely utilized to compute the cross-sectional dispersion of TFP changes (e.g., Lichtenberg (1994), McCunn and Huffman (2000), and Rezitis (2010)). A σ-convergence test measures to what extent TFP levels are becoming more similar across provinces over time, which has the form

$$\operatorname{var}(\ln TFP)_t = \phi_1 + \phi_2 t + \varepsilon_t, \tag{4}$$

where $\operatorname{var}(\ln TFP)_t$ accounts for the variance of TFP in logarithms for all provinces at time t. If ϕ_2 is negative and significantly different from zero, the dispersion of TFPs across provinces is diminishing, and σ-convergence is confirmed.

The second measure is the unconditional β-convergence, which happens if less productive provinces grow faster than more productive ones. This article follows Sala-i-Martin (1996) and Young, Higgins, and Levy (2008) to establish an unconditional β-convergence test with the form

$$\Delta TFP_{it} = \phi_1 + \phi_2 TFP_{i,t-1} + \varepsilon_t, \tag{5}$$

where $TFP_{i,\ t-1}$ is the lagged agricultural productivity and $\Delta TFP_{it} = 100 * (TFP_{it} - TFP_{i,\ t-1})/TFP_{i,\ t-1}$ accounts for the productivity growth in percentage points for province i at time t. A statistically significant negative ϕ_2 indicates that less productive provinces achieved faster growth, which provides evidence of unconditional β-convergence.

The third test is the conditional β-convergence, since some scholars point out that each region converges to its own steady-state productivity level determined by region-specific structural characteristics. A conditional β-convergence occurs when provinces experience β-convergence that is conditional on some other variables. This article introduces a conditional β-convergence test with the form

$$\Delta TFP_{it} = \phi_1 + \phi_2 TFP_{i,t-1} + \delta X_{i,t-1} + \varepsilon_t, \tag{6}$$

where X vectors controlled variables that may affect the growth rate of agricultural productivity, which includes the following: 1) the total sown area that is irrigated, $irrig_{it}$ in logarithms (Jin et al., 2002); 2) the agricultural land area affected by natural disasters (mainly floods and drought), $disaster_{it}$ in logarithms (Gong, 2018a); 3) the rural population ratio completing a high school education, $education_{\mathrm{it}}$ in percentage (Mastromarco & Zago, 2012); 4) public expenditure in agriculture, $expend_{\mathrm{it}}$ in percentage of GDP (Dong, 2000); and 5) the output value shares of forestry ($ratio2_{\mathrm{it}}$), animal husbandry ($ratio3_{\mathrm{it}}$), and fishery ($ratio4_{\mathrm{it}}$) that control the agricultural structural transformation (Gong, 2018c). A conditional β-convergence can be confirmed if ϕ_2 is negative and significantly different from zero.

This paper uses the first two approaches (σ-convergence and unconditional β-convergence) to test whether agricultural convergence has occurred in China since 1978. In order to further investigate the sources of convergence or divergence, this article reconducts σ-convergence tests using disaggregated data at the commodity level and county level, respectively. The result implies which commodities and provinces are converging and which are diverging. The conditional β-convergence test is then utilized to help predict if convergence can be achieved or accelerated when other variables are being considered.

4. Data

Provincial agricultural outputs and inputs of the 31 provinces in mainland China for 1978–2015 are collected from China Statistical Yearbook. This article also collects 23 balanced panels, one for each of China's main farm commodities at the province level from 1985 to 2015, as well as a balanced county-level panel for 1681 counties during the period of 1985–2010. These commodity-level and county-level datasets are collected from the National Cost of Production Data Set and the County-level Agricultural Database by the Ministry of Agriculture and Rural Affairs of China.[2] Since the China Statistical Yearbook also reports data on the controlled variables needed in the conditional β-convergence test, provincial agricultural data is the main dataset. Commodity-level and county-level data only have input and output information and are therefore used as supplementary data in the unconditional tests.

This article follows literature (e.g., Kalirajan et al. (1996), Chen (2006a), Zhou and Zhang (2013), Liu et al. (2015), and Gong (2018a)) in selecting inputs and outputs for China's agricultural sector. The output variable is the deflated gross value of agricultural output (in billions of CNY at 1996 constant prices), which is the sum of agricultural output from farming, forestry, animal husbandry, and fisheries. There are four types of inputs including land (in millions of hectares of sown area), labor (in millions of agriculture labor force), machinery (in millions of kilowatts of total power), and fertilizer (in millions of tons of the gross weight of nitrogen, phosphate, potash, and complex fertilizers).

The China Compendium of Statistics 1949–2008 and provincial-level statistical yearbooks are also utilized to adjust (e.g., data of Chongqing and Hainan) or supplement (e.g., the labor statistics in 2013–2015) the main dataset. It is worth noting that the stock value – rather than the flow value – of public expenditure on agriculture should be used as a TFP determinant, as public expenditure in the current period can affect future TFP as well. This article converts flows data to stocks data using the unified perpetual inventory method (PIM) from Berlemann and Wesselhöft (2014) in order to better estimate the effect of public expenditure and predict a convergence condition.

Table 2 reports summary statistics of the key variables in the main dataset. The provincial average value of agricultural products is 2.2 billion CNY at 1996's constant price, among which farming, forestry, animal husbandry, and fishery account for 60.2%, 4.8%, 28.8%, and 6.2%, respectively. In terms of inputs, these provinces, on average, use a 10 million-strong labor force, 16.1 million kilowatts of agricultural machinery, and 11.7 million tons of fertilizer on 4.9 million hectares of agricultural land, where 35% of the land is irrigated and 29% of the land suffers from natural disaster. Moreover, 15.9% of the rural population completed their high school education and the stock of public expenditure is equivalent to one-third of GDP in the agricultural sector.

5. Estimation results

This section answers three questions in China's agricultural sector based on the three datasets introduced in the previous section: Has agricultural convergence occurred in China during the four decades of reform? If not, what are the sources of this failure to converge? Also, how can this goal be achieved in the future?

[2] http://zzys.agri.gov.cn/nongqingxm.aspx

Table 2
Summary statistics.

Variable name	Notation	Unit	Mean	St. Dev.	Min	Max
Output	*Y*	Billion 1996 CNY	2.2	2.3	0.0	13.4
Land	*Land*	Million hectares	4.9	3.4	0.2	14.4
Labor	*Labor*	Million people	10.0	7.8	0.3	35.6
Machinery	*Machine*	Millions of kilowatts	16.1	20.4	0.2	134
Fertilizer	*Fert*	Million tons	11.7	11.5	0.0	71.6
Irrigated area	*Irrig*	Million hectares	1.7	1.3	0.1	5.5
Disaster area	*Disaster*	Million hectares	1.4	1.2	0	7.4
High school completion rate	*School*	%	15.9	9.9	0.1	62.4
Public expenditure to GDP	*Expend*	%	34	53	0.0	620
Share of forestry	*Ratio*2	%	4.8	4.7	0	51
Share of animal husbandry	*Ratio*3	%	28.8	10.1	8	61
Share of fishery	*Ratio*4	%	6.2	7.6	0	32

5.1. Frontier and productivity estimates

Table 3 presents the estimation results of various SFA models.[3] The first column is the result of a FIX estimator, rather than an RND estimator, according to the Hausman-Wu test ($H = 29.072$, p-value $= .00$). The second to the fourth column provides an estimation of the ECF, CSS, and KSS methods, respectively. The jackknife weights assigned to these four models are 0.0031, 0.0000, 0.4315, and 0.5654, respectively, which implies that most provinces experienced a different and nonlinear trend in productivity, as CSS and KSS models can explain more than 99% of the true DGP. Using these jackknife weights, the fifth column reports the JMA estimator, which is the weighted average of the first four columns. The estimation of JMA shows that labor elasticity and machinery elasticity are the highest, followed by the elasticity of land, whereas the elasticity of fertilizer is the lowest.

Fig. 1 compares the average level of TFP with the highest TFP for each year during the period of 1978–2015 to see if the gap between the two diminishes over time. In literature, many scholars (e.g., Mcmillan et al. (1989), Fan (1991), Lin (1992), Wen (1993), Sicular (1995), Huang (1998), Fan et al. (2002), and Fan et al. (2004)) find that agricultural productivity increased rapidly in the first reform period of 1978–1984, then suffered from significant slowdown in the second period of 1985–1989, after which the productivity continued growing in the 1990s. Fig. 1 shows that the estimated highest TFP and average TFPs are fairly consistent with the trend reported in literature. Moreover, agricultural TFPs suffered from another slowdown in early 2000, which is consistent with the findings in many studies (e.g., Pratt et al. (2008), Dekle and Vandenbroucke (2010), and Wang et al. (2013)). Overall, the agricultural TFP has increased over time, which is a tremendous achievement in China's 40 years of rural reform.

However, the gap between national average TFP and highest TFP is not diminishing over time, which implies that agricututltural convergence seems to not be happening. Moreover, it is necessary to analyze the conditions across regions due to the large differences in economic development and resource endowment among various parts of China (Ahlers, 2019; Gould, 2019; He, Qian, & Ratigan, 2020; Qian, 2019, 2020). Fig. 1 shows that the average TFP in Eastern China is increasing faster and is the most promising region to catch up with the production frontier when compared with Central China and Western China. This result is also consistent with the fact that the coastal area in China has achieved more rapid development than the inland area since the reform and opening up. To summarize, agricultural convergence has not happened in the past four decades based on a basic eyeball check of Fig. 1. This article uses statisical tools to test convergence more precisely, as is explained in the following subsection.

5.2. Agricultural convergence has not occurred

In order to answer the first question of whether convergence has occurred, this paper uses a σ-convergence test and an unconditional β-convergence test. Table 4 reports the estimation of the σ-convergence test in Eq. (4) for the whole country, as well as for each of the three regions, including Western, Central, and Eastern China.[4] The first column indicates that agricultural productivity neither converged nor diverged in China during the last four decades. The second and third columns show that Western and Central China experienced neither convergence nor divergence, which indicates stable productivity gaps among provinces in these two regions. The fourth column shows that the productivity dispersions within Eastern China are decreasing, which implies that most of the provinces in this region are getting closer to the "best practice" province.

Table 5 presents the estimation of the unconditional β-convergence tests in Eq. (5) for the whole country and for each of the three regions. This measure of convergence connects productivity growth to the productivity level, which is ignored in the σ-convergence

[3] The result of the control function test in Amsler et al. (2016) implies that all four inputs are exogenous, which is consistent with the findings in Gong (2018d).

[4] Western China refers to 10 provinces, including Chongqing (重庆), Sichuan (四川), Guizhou (贵州), Yunnan (云南), Tibet (西藏), Shaanxi (陕西), Gansu (甘肃), Qinghai (青海), Ningxia (宁夏), and Xinjiang (新疆). Central China refers to 9 provinces, including Shanxi (山西), Inner Mongolia (内蒙), Jilin (吉林), Heilongjiang (黑龙江), Anhui (安徽), Jiangxi (江西), Henan (河南), Hubei (湖北), and Hunan (湖南). Eastern China refers to 12 provinces, including Beijing (北京), Tianjin (天津), Hebei (河北), Liaoning (辽宁), Shanghai (上海), Jiangsu (江苏), Zhejiang (浙江), Fujian (福建), Shandong (山东), Guangdong (广东), Guangxi (广西), and Hainan (海南).

Table 3
Estimation results of the stochastic frontier models.

	FIX Model	ECF Model	CSS Model	KSS Model	JMA Model
	(1)	(2)	(3)	(4)	(5)
Land	0.229***	0.460***	0.422***	0.170***	0.193***
	(0.037)	(0.037)	(0.007)	(0.025)	(0.010)
Labor	0.733***	0.335***	0.439***	0.640***	0.341***
	(0.042)	(0.044)	(0.007)	(0.033)	(0.010)
Machine	−0.021	0.157***	0.070***	0.125***	0.287***
	(0.024)	(0.033)	(0.006)	(0.026)	(0.008)
Fertilizer	0.059***	0.048***	0.069***	0.065***	0.030***
	(0.019)	(0.014)	(0.004)	(0.012)	(0.005)
Jackknife w_m^*	0.0031	0.0000	0.4315	0.5654	–

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. Data of 31 provinces in mainland China for 1978–2015 are collected from China Statistical Yearbook. Sample size is 1178.

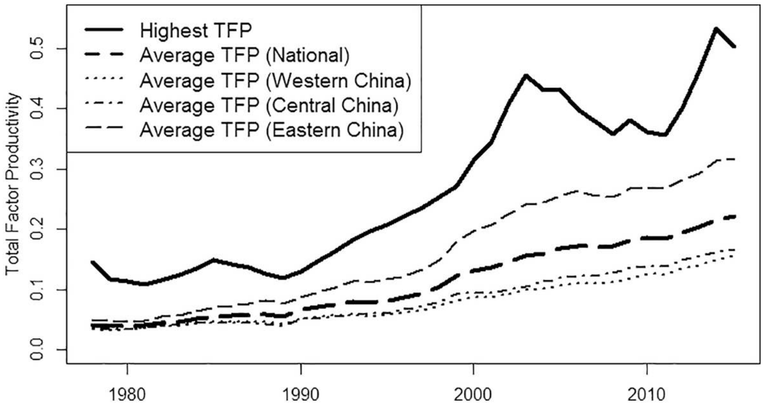

Fig. 1. Highest TFP and average TFPs in China's agricultural sector, 1978–2015.

Table 4
Estimation results of σ-convergence tests.

	All regions	Western China	Central China	Eastern China
	(1)	(2)	(3)	(4)
Time trend	0.003	−0.0001	0.0003	−0.0012**
	(0.006)	(0.0002)	(0.0002)	(0.0004)
Intercept	−5.831***	1.442**	−0.513	2.411**
	(1.092)	(0.420)	(0.491)	(0.778)
Conclusion	neither	neither	neither	converge

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. Data of 31 provinces in mainland China for 1978–2015 are collected from China Statistical Yearbook. Sample size is 37, one for each year from 1979 to 2015.

test. For all 31 of the Chinese provinces, the first column in Table 5 concludes with neither convergence nor divergence, which indicates that less productive provinces, on average, achieved the same productivity growth as more productive provinces. Moreover, the same conclusion can be made for Western China and Central China, according to the second and third columns. Finally, unconditional convergence is witnessed in Eastern China since the laggards developed faster than the leaders in agricultural productivity within that region. To summarize, the conclusions from the σ-convergence test and unconditional β-convergence test are fairly consistent; both imply that agricultural convergence has not occurred in the last four decades.

5.3. Sources of the failure to converge

Using provincial data, the previous subsection fails to investigate the convergence condition within each province. Counties in the same province find it easier to catch up because of more technology spillovers and fewer policy restrictions, which is an important

Table 5
Estimation results of unconditional β-convergence tests.

	All regions	Western China	Central China	Eastern China
	(1)	(2)	(3)	(4)
$\ln TFP_{t-1}$	−0.732	−0.739	−0.957	−1.706**
	(0.393)	(0.788)	(1.040)	(0.563)
Intercept	2.767**	2.177	1.581	1.672
	(0.994)	(2.160)	(2.808)	(1.237)
Sample Size	1111	351	333	427
Conclusion	neither	neither	neither	converge

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. Data of 31 provinces in mainland China for 1978–2015 are collected from China Statistical Yearbook.

Table 6
Estimation results of σ-convergence tests by province.

Province name	σ-convergence tests		Region
	Estimates	SE	
Group 1: Convergence			
Hainan (海南)	−0.007***	(0.001)	Eastern
Inner Mongolia (内蒙)	−0.017***	(0.003)	Central
Anhui (安徽)	−0.0017***	(0.0003)	Central
Ningxia (宁夏)	−0.0057*	(0.003)	Western
Qinghai (青海)	−0.0035*	(0.001)	Western
Group 2: Divergence			
Liaoning (辽宁)	0.022*	(0.011)	Eastern
Zhejiang (浙江)	0.010***	(0.001)	Eastern
Shandong (山东)	0.006**	(0.002)	Eastern
Shanxi (山西)	0.021***	(0.005)	Central
Heilongjiang (黑龙江)	0.0079***	(0.002)	Central
Hubei (湖北)	0.0039***	(0.001)	Central
Hunan (湖南)	0.0035**	(0.001)	Central
Jilin (吉林)	0.0028**	(0.001)	Central
Tibet (西藏)	0.0097***	(0.002)	Western
Shaanxi (陕西)	0.0055***	(0.001)	Western
Guizhou (贵州)	0.005***	(0.001)	Western
Yunnan (云南)	0.0046***	(0.0005)	Western
Sichuan (四川)	0.0037*	(0.001)	Western
Group 3: Neither			
Hebei (河北)	0.0014	(0.0011)	Eastern
Jiangsu (江苏)	0.0008	(0.002)	Eastern
Fujian (福建)	−0.0046	(0.005)	Eastern
Guangdong (广东)	0.0036	(0.003)	Eastern
Guangxi (广西)	0.0002	(0.001)	Eastern
Jiangxi (江西)	0.0018	(0.001)	Central
Henan (河南)	0.0015	(0.001)	Central
Chongqing (重庆)	0.0011	(0.001)	Western
Gansu (甘肃)	−0.0005	(0.001)	Western
Xinjiang (新疆)	0.0038	(0.002)	Western

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. A balanced county-level panel for 1681 counties during the period of 1985–2010 is collected from the County-level Agricultural Database by the Ministry of Agriculture and Rural Affairs of China. The sample size is 60,516. The convergence tests for Beijing, Tianjin, and Shanghai are not reported due to sample size limit.

approach to improve provincial TFP at an aggregated level and to lead to convergence. In order to closely observe the within-province catch-up condition, this paper estimates county-level agricultural TFP and tests convergence for each province. This article collects county-level input and output data from the County-level Agricultural Database by the Ministry of Agriculture and Rural Affairs of China. Table 6 reports the estimation of the σ-convergence test of each province based on a balance panel of 1681 counties from 1985 to 2010. Table 6 shows that agricultural convergence has occurred in only five provinces, including Hainan, Inner Mongolia, Anhui, Ningxia, and Qinghai, whereas the remaining 23 provinces have not achieved convergence. When using provincial data, Table 4 indicates that Eastern China achieved σ-convergence, whereas Western China and Central China did not. Although the advantage of Eastern China is not obvious in the convergence group in Table 6, the disadvantages of Western China and Central China in the divergence group are relatively clear: there are only one third of the provinces in Eastern China witnessed divergence but more

Table 7
Estimation results of σ-convergence tests by commodity.

Commodity name	σ-convergence tests		Classification
	Estimates	SE	
Group 1: Convergence			
Field cucumber	−0.0091*	(0.0036)	Crops
Field tomato	−0.0052**	(0.0017)	Crops
Beef	−0.0042***	(0.0009)	Livestock
Hog	−0.0006*	(0.0003)	Livestock
Group 2: Divergence			
Early indica rice	0.0013***	(0.0002)	Crops
Middle indica rice	0.0011***	(0.0003)	Crops
Wheat	0.0004*	(0.0002)	Crops
Corn	0.0017**	(0.0005)	Crops
Group 3: Neither			
Late indica rice	0.0004	(0.0003)	Crops
Japonica rice	−0.0004	(0.0006)	Crops
Soybean	0.0234	(0.055)	Crops
Cotton	−0.0004	(0.0004)	Crops
Canola	0.0002	(0.0004)	Crops
Capsicum	−0.0001	(0.0026)	Crops
Eggplant	0.0027	(0.0020)	Crops
Greenhouse cucumber	0.0007	(0.0017)	Crops
Greenhouse tomato	−0.0063	(0.0046)	Crops
Peanuts	0.0004	(0.0010)	Crops
Sugar beet	0.0012	(0.0014)	Crops
Sugar cane	−0.00005	(0.0003)	Crops
Broiler	−0.0006	(0.0012)	Livestock
Egg	−0.0002	(0.0002)	Livestock
Milk	−0.0005	(0.0005)	Livestock

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. 23 balanced panels, one for each of China's main farm commodities at the province level, are collected from the National Cost of Production Data Set. The data covers the period from 1985 to 2015 for Early Indica Rice, Middle Indica Rice, Late Indica Rice, Japonica Rice, Wheat, Corn, Soybean, Cotton, and Canola. The data covers the period from 1995 to 2015 for the remaining commodities.

than half of the provinces in Western China and Central China experienced divergence. It is worth noting that the results of the convergence tests in Table 4 and Table 6 are not directly comparable. However, Table 6 implies that more counties in the lagging areas (Western China and Central China) are moving away from provincial frontier, let alone regional frontier or national frontier. As a result, Western China and Central China haven't achieved convergence, which can be the main reason of the failure to convergence for the country as a whole.

On the other hand, technology spillovers and catch-up may be easier to achieve for the same farm commodity. The second investigation is to explore within-commodity convergence by disaggregating agricultural data to various farm commodities. This article collects provincial data for 23 of China's main farm commodities from the National Cost of Production Data Set. Table 7 presents the estimation of the σ-convergence test for each of the 23 commodities. The result indicates that two crops and two livestock commodities, including field cucumber, field tomato, beef, and hog, are on the right track to convergence. The second source of failure to convergence is due to the remaining 19 farm commodities, especially early indica rice, middle indica rice, wheat, and corn in the divergence group.

China invests substantially on the R&D and the turnover rate of some varieties (e.g., rice, wheat and corn) is comparatively high. These factors can accelerate technological progress and hence shift the frontier. It is worth noting that divergence in TFP doesn't mean TFP or its growth is declining. It only indicates that the frontier and leading areas are growing faster than the lagging areas. In the context of a successful research system that improves the frontier dramatically, the lagging areas are harder to catch up without a strong extension system to spread the new technologies. Moreover, provincial extension system and lower-level extension system are only responsible for the technology diffusion within its own area, which makes commodity-specific technology spread across the border so difficult. As a result, within-commodity convergence has not been achieved across provinces, which implies that China needs a stronger extension system, especially at national level, to better implement cross-region technology spillovers and achieve convergence.

5.4. Possibility of future convergence

China is not on the right track toward agricultural convergence, since 23 out of 28 provinces and 19 out of 23 farm commodities

Table 8
Estimation results of conditional β-convergence tests.

	All regions	Western China	Central China	Eastern China
	(1)	(2)	(3)	(4)
$\ln TFP_{t-1}$	−5.738***	−5.603*	−13.958***	−8.792***
	(1.126)	(2.234)	(3.704)	(1.919)
$\ln irrig_{t-1}$	0.775*	2.048**	1.209	−0.589
	(0.422)	(0.746)	(1.463)	(0.768)
$\ln disaster_{t-1}$	0.265	0.103	1.452	0.827
	(0.269)	(0.581)	(1.211)	(0.467)
$education_{t-1}$	0.158***	0.122	0.405*	0.188
	(0.044)	(0.109)	(0.204)	(0.124)
$finance_{t-1}$	4.810**	7.625*	−3.581	2.386
	(1.987)	(3.395)	(6.498)	(3.678)
$ratio2_{t-1}$	0.066	−0.074	−0.054	0.143
	(0.079)	(0.206)	(0.241)	(0.122)
$ratio3_{t-1}$	0.098**	0.116*	0.136	0.166*
	(0.035)	(0.057)	(0.102)	(0.075)
$ratio4_{t-1}$	0.326***	0.241	0.351*	0.363***
	(0.054)	(0.403)	(0.152)	(0.098)
Intercept	−32.261***	−41.934***	−75.619***	−33.097***
	(4.839)	(10.203)	(17.398)	(9.535)
Sample size	1111	351	333	427
Conclusion	converge	converge	converge	converge

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. Data of 31 provinces in mainland China for 1978–2015 are collected from China Statistical Yearbook.

have failed to converge. Table 8 reports the estimation of the conditional β-convergence tests in Eq. (6), which explores whether it is possible to converge in the future.

When other variables are held constant, β-convergence in agricultural productivity is witnessed for the whole country and for each of the three regions. Moreover, Central China can achieve the highest speed of convergence, followed by provinces in Eastern China, whereas the conditional convergence speed is the lowest in Western China. The regression results in Table 8 also imply a means to improve the productivity growth rate to accelerate convergence. Overall, broader irrigation systems, higher education in rural areas, greater agricultural public expenditure, and a larger share of animal husbandry and fishery in the agriculture sector all have significantly positive effects on agricultural productivity growth. The result of these conditional β-convergence tests indicates the possibility of agricultural catch-up if lagging provinces can receive better support in the aforementioned four aspects as the leading provinces do.

The results of the conditional β-convergence tests show that improvement in irrigation, education, public expenditure, and structural transformation can diminish the productivity gap and help to achieve catch-up. This article further explores whether the lagging regions (Western and Central China) have lower levels in these four aspects than the leading region (Eastern China). Table 9 reports the levels and changes of irrigation rate, high school completion rate, public expenditure to GDP ratio, and value share of animal husbandry and fishery segments by region.

Overall, Western China and Central China are at a lower level and have less growth in most of these four ratios than Eastern China. Therefore, Western China and Central China have the potential to increase their agricultural productivity growth rate if these

Table 9
Levels and changes of TFP growth drivers by region.

		1978–2015 Average	1978 Average	2015 Average	1978–2015 Change
Irrigation rate	Western	0.37	0.35	0.41	0.06
	Central	0.30	0.26	0.39	0.13
	Eastern	0.42	0.36	0.49	0.13
Rural high school completion rate	Western	0.12	0.05	0.25	0.20
	Central	0.15	0.08	0.30	0.22
	Eastern	0.20	0.11	0.35	0.24
Public expenditure to GDP ratio	Western	0.40	0.10	0.94	0.84
	Central	0.22	0.05	0.72	0.67
	Eastern	0.25	0.04	0.72	0.67
Share of animal husbandry & fishery	Western	0.33	0.26	0.34	0.09
	Central	0.32	0.16	0.39	0.23
	Eastern	0.39	0.18	0.43	0.25

Note. Data of 31 provinces in mainland China for 1978–2015 are collected from China Statistical Yearbook, and adjusted by the China Compendium of Statistics 1949–2008 and provincial-level statistical yearbooks.

four ratios can be improved at the same or an even faster pace than Eastern China. Moreover, even for the developed region of Eastern China, a faster speed of convergence can be achieved if those that lag within the region can improve these four aspects, as the coefficient of $\ln TFP_{t-1}$ in the fourth column of Table 8 (−8.792) is much more negative than the one in Table 5 (−1.706).

5.5. Robustness checks

The first concern is about the functional form. The baseline agricultural TFPs are computed using the Cobb-Douglas stochastic frontier estimates in Table 3, which is denoted as ${TFP_{it}}^{CD}$. On the one hand, this article estimates agricultural TFPs using conventional production function (denoted as ${TFP_{it}}^{CPF}$) rather than stochastic frontier model to see if consistent results hold. On the other hand, this article employs a Transcendental Logarithmic (translog) stochastic frontier model (denoted as ${TFP_{it}}^{TL}$) to check the robustness of the baseline estimates.

Second, China's agriculture includes four segments (farming, forestry, animal husbandry, and fisheries), each may has its own production function. In early years, scholars pay most attention only on farming segment since it dominated agriculture. As a result, most of the existing studies assumes a unique production frontier for agriculture and ignores inputs of animal husbandry and fisheries. However, as animal husbandry and fisheries segments are expanding in recent years, it is necessary to take heterogeneity in agricultural output into consideration. On the one hand, this article still follows existing studies in production frontier assumption and input selection in the baseline model to make our estimates comparable with those in literature (e.g., Kalirajan et al. (1996), Chen (2006a), Zhou and Zhang (2013), Liu et al. (2015)). On the other hand, this article adopts the varying coefficient model in Gong (2018a), where the production frontier changes as the revenue shares of farming, forestry, animal husbandry, and fisheries change. As a result, the structural transformation and heterogeneity of output across provinces and over time are controlled. Moreover, besides the four inputs (labor, land, fertilizer, and machinery), this article also puts three livestock-related and aquacultural inputs into the production frontier model, including livestock capital,[5] grassland area, and aquaculture area.

Third, all stochastic frontier models employed in this article first estimate efficiency and productivity and then estimate the impact of other variables (such as education and irrigation) in the second-step conditional convergence test. In literature, some scholars tend to incorporate variables that may affect inefficiency levels, such as education and irrigation, in the inefficiency equation and measure them simultaneously with the production function, which is also known as the one-step approach. This article adopts the most widely used one-step approach, the BC95 model (Battese & Coelli, 1995), to check if the TFP estimates are robust with the ones in the baseline model. In our BC95 model, we assume all the control variables used in the conditional convergence test can affect inefficiency term.

Table 10 compares the TFPs derived from various models through two approaches. First, this article regress each of the alternative TFPs on the baseline TFP to see if the coefficients are both statistically and economically significant. Second, this article calculates the correlation coefficients of the baseline TFP with each of the alternative TFPs to check if they are highly correlated. The results of all six columns verify the robustness of our baseline model, as the coefficients of ${TFP_{it}}^{CD}$ in all six columns are both statistically and economically significant. Moreover, the correlation coefficients in all six columns are above 0.7, which indicates a significant positive linear relationship across models and further confirms the robustness of the baseline model.

In terms of the convergence test, this article also establishes two robustness checks. On the one hand, we use unit root tests to minimize the potential of a spurious regression. Following Ball, Hallahan, and Nehring (2004), this article adopts the panel unit root test proposed by Levin and Lin (1992) and the panel unit root test proposed by Im, Pesaran, and Shin (2003), both are described in detail in Levin, Lin, and Chu (2002). According to the test statistics reported in Table 11, this article rejects the null hypothesis of a unit root and thus can employ the convergence tests assuming stationarity.

On the other hand, our baseline model calculates the TFP growth rates using data from two successive periods. Some scholars calculate TFP growth rates using a longer time interval, since the TFP growth rate from year to year could be volatile in responding to some transitory events. This article follows the panel estimates approaches in Sala-i-Martin (1996) to checks the robustness of the results in our baseline model. Using data of 48 U.S. states for the period 1880 to 1990, Sala-i-Martin (1996) divides of the overall period into sets of ten-year pieces. In the β-convergence test, the dependent variable is the average TFP growth rate for each ten-year pieces, whereas the independent variables are the initial levels of each ten-year pieces. This article also divides the dataset into sets of ten-year pieces. Then ten year average TFP growth rates are calculated as the dependent variable and regressed on the initial values of the independent variables in the corresponding ten-year period. Since our dataset covers a shorter period of 38 years, we also divide the overall period into sets of five-year pieces and re-calculate the panel estimates. Table 12 compares the estimations of our baseline model with the ones using a five-year interval and the ones using a ten-year interval. All three approaches deliver consistent conclusion that agricultural convergence has not occurred but is still attainable in the future, which confirms the robustness of our baseline estimates.

[5] The inclusion of livestock capital as an input for livestock segment is suggested by the Food and Agriculture Organization of the United Nations (FAO) and the Economic Research Service of the United States Department of Agriculture (USDA-ERS). This article follows USDA-ERS by calculating the total livestock capital on farms in "cattle equivalents". Stocks of end-of-year inventories for different livestock species are collected from China Statistical Yearbook. Weights for each species are from Hayami and Ruttan (1985), which makes it possible to convert all species in "cattle equivalents".

Table 10
Robustness of the TFPs across models.

	TFP_{it}^{CPF}	TFP_{it}^{TL}	TFP_{it}^{VC}	TFP_{it}^{CD7}	TFP_{it}^{VC7}	TFP_{it}^{BC95}
	(1)	(2)	(3)	(4)	(5)	(6)
TFP_{it}^{CD}	0.798***	0.879***	0.827***	0.861***	0.732***	0.781***
	(0.015)	(0.016)	(0.012)	(0.006)	(0.016)	(0.019)
Constant term	−2.364***	−0.464***	0.458***	0.640***	1.208***	1.209***
	(0.011)	(0.040)	(0.009)	(0.004)	(0.012)	(0.028)
Correlation	0.845	0.848	0.888	0.973	0.800	0.794

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively. TFP_{it}^{CD} refers to the TFP estimates derived from the baseline model, TFP_{it}^{CPF} refers to the TFP estimates derived from the conventional production function, TFP_{it}^{TL} refers to the TFP estimates derived from the translog stochastic frontier model, TFP_{it}^{VC} refers to the TFP estimates derived from the varying coefficient stochastic frontier model, TFP_{it}^{CD7} refers to the TFP estimates derived from the baseline model with seven inputs, TFP_{it}^{VC7} refers to the TFP estimates derived from the varying coefficient stochastic frontier model with seven inputs, and TFP_{it}^{BC95} refers to the TFP estimates derived from the one-step stochastic frontier model (Battese & Coelli, 1995) where irrigated area, disaster area, high school completion rate, public expenditure to GDP, and agricultural structural transformation can affect inefficiency level. Sample size is 1178.

Table 11
Robustness of the TFPs across models.

Variable	Levin and Lin's test statistics	Im, Pesaran, and Shin's test statistics
ΔTFP_{it}	−25.91	−27.83
TFP_{it}	−20.35	−19.78
$disaster_{t-1}$	−5.45	−3.21
$education_{t-1}$	−4.04	−4.41
$finance_{t-1}$	−2.04	−2.50
$ratio2_{t-1}$	−3.97	−3.80
$ratio3_{t-1}$	−5.85	−4.07
$ratio4_{t-1}$	−7.78	−4.63

Note. This table reports the z score, where the 5% critical value = 1.65.

Table 12
Robustness of the β-convergence tests across Models.

	Unconditional β-convergence tests			Conditional β-convergence tests		
	Annual ΔTFP_{it}	5 Years Average ΔTFP_{it}	10 Years Average ΔTFP_{it}	Annual ΔTFP_{it}	5 Years Average ΔTFP_{it}	10 Years Average ΔTFP_{it}
$\ln TFP_{t-1}$	−0.732	−0.859	−0.618	−5.738***	−4.891***	−3.776***
	(0.393)	(0.576)	(0.439)	(1.126)	(0.862)	(0.730)
$\ln irrig_{t-1}$	–	–	–	0.775*	0.625**	0.554*
	–	–	–	(0.422)	(0.312)	(0.288)
$\ln disaster_{t-1}$	–	–	–	0.265	0.065	0.064
	–	–	–	(0.269)	(0.113)	(0.099)
$education_{t-1}$	–	–	–	0.158***	0.160***	0.139***
	–	–	–	(0.044)	(0.044)	(0.035)
$finance_{t-1}$	–	–	–	4.810**	4.801**	4.698***
	–	–	–	(1.987)	(1.985)	(1.986)
$ratio2_{t-1}$	–	–	–	0.066	0.098*	0.100***
	–	–	–	(0.079)	(0.054)	(0.026)
$ratio3_{t-1}$	–	–	–	0.098**	0.117***	0.136
	–	–	–	(0.035)	(0.032)	(0.044)
$ratio4_{t-1}$	–	–	–	0.326***	0.264***	0.213***
	–	–	–	(0.054)	(0.052)	(0.047)
Intercept	2.767**	2.403***	2.890***	−32.261***	−20.03***	−16.11***
	(0.994)	(0.920)	(0.989)	(4.839)	(4.415)	(3.558)
Sample size	1,111	217	124	1,111	217	124
Conclusion	neither	neither	neither	converge	converge	converge

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 0.1%, 1%, and 5% levels, respectively.

6. Conclusion and policy implications

This article aims to answer three questions: Has agricultural convergence occurred in China during the four decades of reform? If not, what are the sources of this failure to converge? Also, how can this goal be achieved in the future? Four methods to derive TFP are given, but none of them alone can fully explain the trend of agricultural productivity for various provinces over time. As a result, a jackknife model averaging method is adopted so that all these methods are jointly considered to estimate a more accurate provincial TFP in agriculture. This article then introduces three convergence tests to answer the three aforementioned questions. To our best knowledge, this is the first study to employ a model averaging method to test China's agricultural convergence, as well as the first study to test province-level and commodity-level convergence.

Using a balanced panel of 31 provinces from 1978 to 2015, this article finds that the agricultural productivity trend is indeed non-linear and province-specific, and both the parametric CSS and semi-parametric KSS models are indispensable to explain the true data generating process, which, in turn, highlights the necessity of using a model averaging method. This article concludes that σ-convergence has not been achieved in China, which is consistent with the results in Wang et al. (2019). Although agricultural convergence has not occurred, it is still attainable in the future since evidence of conditional β-convergence has been found, which is consistent with the findings in Ma and Feng (2013) and Wang et al. (2019). Moreover, this article finds that improvements in irrigation, education, public expenditure are effective channels to diminish the productivity gap, in addition to the expansion of animal husbandry and fishery segments. Besides estimating the overall convergence as in literature, this article also investigates convergence conditions at commodity-level and county-level. We find that 23 out of 28 provinces and 19 out of 23 farm commodities failed to converge, according to a convergence test using county-level panel data for 1861 counties and commodity-level panel data for 23 farm commodities.

Although the government has significantly increased transfer payment, the levels of irrigation and education in Central China and Western China are still much lower than those in Eastern China. Without improvement in irrigation, education, public expenditure and livestock-related industries, agricultural productivity in lagging areas may unable to converge. Moreover, within-province and with-commodity convergence are very important in achieving overall convergence in agricultural sector. China's research system has been able to deliver remarkable technology innovation to accelerate technological progress. However, in order to achieve convergence, agricultural research system and extension system in each province and for each commodity need to do a better job in technology diffusion and spread. At the same time, the counterpart support between leading areas and lagging areas (such as counterpart support to Xinjiang and Tibet) are of great significant to cross-province convergence. Last but not least, the rural revitalization strategy in China highlighted the importance of agricultural modernization. Agricultural productivity convergence in lagging areas is a must-have if China wants to achieve comprehensive revitalization in 2050.

Acknowledgements

Binlei Gong acknowledges support by the National Natural Science Foundation of China (71903172), the Research Program for Humanities and Social Science Granted by Chinese Ministry of Education (18YJC790034), the Soft Science Research Program of Zhejiang Province (2020C25020), Qianjiang Talent Program, and Academy of Social Governance at Zhejiang University.

Declarations of Competing Interest

None.

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