Food Policy 117 (2023) 102446

Contents lists available at ScienceDirect

Food Policy

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

Interplay between China's grain self-sufficiency policy shifts and interregional, intertemporal productivity differences

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ARTICLE INFO

Keywords:
Meta-frontier function
Output distance function
Agricultural policy shift
Convergence
Technological gap

ABSTRACT

In 2013, the Communist Party of China decided to partially relax its self-sufficiency targets for grain, historically first recognizing moderate imports as a policy option for ensuring food security in the country. This study empirically examines the interplay between the policy shifts and the interregional, intertemporal productivity differences in Chinese agriculture. It employs a meta-frontier stochastic output distance function approach. Our empirical result shows that input augmentation was the main contributor to the agricultural output growth during 1984–2000, whereas total factor productivity is the main driver of the growth during 2001–2020. This lends strong support to an argument in the literature that Chinese crop production has recently transformed from a resource-input-driven activity to one driven by science and technology. Our study also demonstrates that the western region, which far lagged behind others in the past in terms of agricultural technology, has made remarkable progress during 2001–2020, which confirms the cross-regional productivity convergence over time. It is likely that farmers in this region were better able to gain a higher economic return from crop diversification into horticulture, for which they might have been all the more motivated to improve their productivity.

1. Introduction

Ensuring food security for its citizens is one of the most important political and economic challenges of many national governments. The World Food Summit convened in Rome in 1996 adopted the following declaration: "Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO, 1996). Although the declaration and its annexes do not include the term "self-sufficiency," some countries replace "food security" with "grain self-sufficiency" or "staple food self-sufficiency" and make it a national policy goal (Clapp, 2017).

China officially announced a 95% grain self-sufficiency rate as the bottom line of its food security in 1996 (Zhang and Cheng, 2017). Furthermore, an official document issued by the State Council of the People's Republic of China in 2008 reiterated the adherence to grain self-sufficiency at the level of 95% and the securement of farmland for that purpose (Ito and Ni, 2013). However, China's rapid economic growth and urbanization, accompanied by an agrarian structural transformation and a drastic change in people's dietary habits, have jeopardized the realization of the long-held policy goal. Zhang and Cheng (2017) argue that China's grain self-sufficiency policy has proven to be too costly and generates considerable pressure on the domestic environment, which poses a grave threat to the long-term sustainability of agriculture. Confronted by these challenges, the Communist Party of China decided in 2013 to partially relax its self-sufficiency targets for grain, historically first recognizing moderate imports as a policy option for ensuring food security in the country.[1]

This study's primary objective is to show that China has shifted its grain self-sufficiency policy from a nationally uniform program to a regionally differentiated one, and then, to empirically examine the interplay between the policy shifts and the interregional, intertemporal productivity differences in agriculture. Song et al. (2021) assert that policy-oriented forces to maintain grain self-sufficiency played a leading role in Chinese agriculture in the long term. However, the past decade witnessed signs of change in this policy orientation. The government has

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[1] Using Global Food Security Index (GFSI), Chen et al. (2016) explore the relationship between Taiwan's trade liberalization and food security status (the GFSI considers food affordability, availability, quality and safety, and sustainability and adaptation). Their analysis suggests that Taiwan's trade liberalization reduced its food self-sufficiency rate, but conversely improved food security. This is consistent with the widely accepted view that food self-sufficiency does not guarantee domestic food security and trade liberalization is an important adaptive strategy to combat climate change-induced instability in agricultural production.

https://doi.org/10.1016/j.foodpol.2023.102446
Received 11 October 2022; Received in revised form 23 March 2023; Accepted 24 March 2023
Available online 17 April 2023
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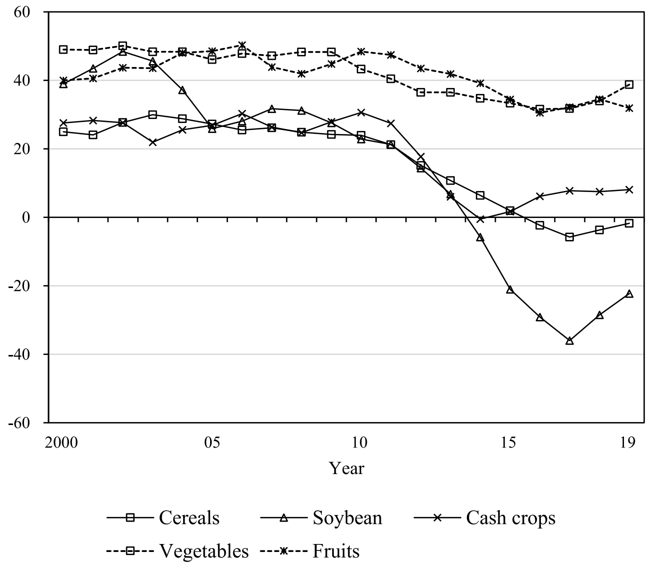

Fig. 1. Change in profit margins by crop (%). Source: National Agricultural Product Cost-Benefit Data Compilation (The National Development and Reform Commission). Note: The statistics report the average agricultural revenues and total costs of 60,000 farm households in 1,553 counties by crop. Cereals are rice, wheat, and maize, while cash crops are oil crops, cotton, sugarcane, and beetroots. Cash crops and fruits are computed by the weighted average of profit margins, using production quantity data at the national level.

assigned grain production targets to some provinces, whereas farmers in other provinces are encouraged to diversify their crop choice, thus increasing their farm income. This policy change is meant not only to maintain national grain self-sufficiency at a certain level but also to narrow the interregional farm income disparity. Policy initiatives are undoubtedly the main drivers of grain production growth, but crop diversification based on profit motives is gaining momentum in some regions of China.

Methodologically, we estimate a *meta*-frontier output distance function (ODF) to accommodate the potential heterogeneity in the production environment and technological gaps across regions (Battese et al., 2004). The literature increasingly employs the *meta*-function approach based on a stochastic model to analyze the economic performance of agriculture (Alem et al., 2019; Boshrabadi et al., 2008; Bravo-Ureta et al., 2020; DeLay et al., 2022; Geffersa et al., 2022; Khanal et al., 2018; Lawin and Tamni, 2019; Liu et al., 2021; Melo-Becerra and Orozco-Gallo, 2017; Nguyen et al., 2021; Owusu and Bravo-Ureta, 2022). The *meta*-frontier approach has the advantage over a "traditional model" (which estimates a stochastic function based on pooled data) in that one can estimate technical efficiency without assuming the same technology for all sample observations. The core challenge of this model is to identify the technological gap between the region-specific frontier and *meta*-frontier functions (Battese et al., 2004; O'Donnell et al., 2008).

Our contribution to the literature is to provide empirical insights into whether/how marginalized regions catch up with advanced regions with regard to agricultural technology. The Achilles' heel in the Chinese economy is the backwardness of the western region; such regional gaps are an ongoing concern for development policies in other countries as well.[2] In a country such as China with a large territory, it is of particular importance to distinguish between intra- and interregional productivity disparities to accurately diagnose the cause of this problem. The *meta*-frontier model is most suitable for this purpose, but few attempts have been made on this issue. Our study, therefore, bridges this gap in the literature by focusing on China's interregional and intertemporal differences in agricultural productivity.

The remainder of this paper is organized as follows. Section 2 provides the background on agricultural policy and production in China, with special emphasis on the transformed grain self-sufficiency policies. Section 3 outlines the theoretical consideration of the *meta*-frontier production function and stochastic ODF and the data processing required for the econometric analysis. Section 4 presents the estimation results. Section 5 concludes the study with a summary of the findings and policy implications.

2. Agricultural policy and production in China

2.1. A shift of policy goals

In 1995, China's central government launched the "governor's grain bag responsibility system," which placed the onus on provincial leaders to secure the grain needed in their province and stabilize the local grain market (Tuan and Ke, 1999). Carter and Lohmar (2002) claim that the system was effective in increasing grain-sown areas in both grain-surplus and grain-deficit provinces and, therefore, helped boost the total grain production. They argue, however, that this interventionist policy incurred economic costs in Chinese agriculture. Furthermore, the State Council of the People's Republic of China published a document entitled "The medium- and long-term plan for national food security" in the wake of the 2007–2008 international food crisis. The document referred to maintaining a 95% grain self-sufficiency rate and securing agricultural land for that purpose. Thus, the top priority in China's agricultural policy at that time was to ensure food security by maintaining a high grain self-sufficiency rate.

However, this policy goal has gradually become difficult to achieve. First, rising production costs have reduced the international competitiveness of Chinese agriculture (Huang and Yang, 2017), and second, drastic changes in the food preferences of citizens have significantly increased the demand for feed grains and oilseed crops. China was a net exporter of maize until the 1990 s, but since 2009, it has become a constant importer, with the import volume reaching 28 million tons in 2021 (consequently, China has become the world's largest importer of maize). Soybean imports have surged since the late 1990 s, accounting for over 60% of global imports in 2020. In response to these changing circumstances, China's central government issued the Number One Document in 2014, declaring the break away from full self-sufficiency to a new food security strategy – one that relies on domestic production with moderate imports (Zhang and Cheng, 2017). In stark contrast, the domestic production of vegetables and fruits has grown rapidly over the past 30 years, reaching 0.84 billion tons in 2020, which is 1.36 times larger than that of cereals (FAOSTAT).[3] Additionally, since 2010, China has overtaken Spain to become the world's largest exporter of vegetables.

A significant increase in vegetable and fruit production reflects changes in consumer diets (Lichtenberg and Ding, 2008). However, China has a comparative advantage in growing labor-intensive crops such as horticultural products (Lu, 1998; Zhang and Cheng, 2017). Fig. 1 illustrates a change in the profit margins by crop during 2000–2019 (the three-year moving average). The profit margins, defined as profits (revenues minus costs) divided by revenues, are computed from the data of a household survey conducted by the National Development and Reform Commission. The central government introduced supportive

[2] China's central government launched the Great Western Development Project in 2000 to narrow the economic disparity between the western and non-western regions (Jia et al., 2020). The main policy measure adopted for this purpose was large-scale investments in infrastructure.

[3] In 1990, the domestic production of vegetable and fruit (by weight) was less than 37% of cereals.

Table 1
Interregional differences in agricultural productivity and growth.

	National	Eastern	Central	Western
Average per capita disposal income of rural households (AIRHs) in 2020 (yuan)	17,132	20,422	16,224	13,753
The ratio of wage income to the AIRHs in 2020 (%)	40.7	48.5	35.6	33.5
Share of the rural population in 2020 (%)	36.1	30.4	39.9	43.0
Share of primary industry's gross output value in 2020 (%)	8.01	5.65	10.65	11.76
1984–2000				
Production share of Sector 1 (%)	55.4	46.6	64.7	58.9
Sector 2 (%)	12.6	15.3	8.3	13.9
Sector 3 (%)	32.1	38.1	27.0	27.2
Labor productivity: Y/L (ton/person)	4.22	5.71	4.06	2.76
Land productivity: Y/A (ton/ha)	5.38	7.12	4.49	4.48
Land-labor ratio: A/L (ha/person)	0.78	0.79	0.90	0.62
The growth rate of real agricultural output value (%)	4.9	5.0	4.5	5.5
The growth rate of agricultural production: Y (%)	4.5	4.8	4.3	4.3
Sector 1 (%)	1.7	1.2	2.1	2.0
Sector 2 (%)	3.3	2.6	2.3	6.0
Sector 3 (%)	10.4	10.6	10.8	9.1
The growth rate of Y/L (%)	4.4	5.8	4.1	3.0
The growth rate of Y/A (%)	3.9	4.6	3.8	2.7
The growth rate of A/L (%)	0.5	1.2	0.3	0.3
2001–2020				
Production share of Sector 1 (%)	36.8	26.0	50.4	36.2
Sector 2 (%)	10.5	14.7	4.7	12.0
Sector 3 (%)	52.6	59.3	44.9	51.9
Labor productivity: Y/L (ton/person)	10.91	15.13	10.82	6.89
Land productivity: Y/A (ton/ha)	9.43	13.84	7.48	7.64
Land-labor ratio: A/L (ha/person)	1.13	1.07	1.40	0.88
The growth rate of real agricultural output value (%)	4.2	3.0	4.3	6.2
The growth rate of agricultural production: Y (%)	2.8	1.9	3.2	4.0
Sector 1 (%)	2.4	1.4	3.5	1.5
Sector 2 (%)	1.4	1.7	0.6	1.3
Sector 3 (%)	3.3	2.3	3.1	6.6
The growth rate of Y/L (%)	5.8	5.5	6.6	6.1
The growth rate of Y/A (%)	2.3	2.3	2.2	3.1
The growth rate of A/L (%)	3.6	3.2	4.3	3.1

Source: Provincial Statistical Yearbook.
Note: Owing to the lack of data, the growth rate of agricultural real output value could not be computed for 1984–2000.

programs for grain producers in the mid-2000 s.[4] Nevertheless, vegetable and fruit cultivation has yielded much higher returns than other crops, which might have motivated many farmers to convert to horticultural production.[5] To restrict such a movement, the government announced a plan in 2009 to increase grain production, mainly in the central provinces, such as Anhui, Jiangxi, Henan, Hubei, and Hunan, by 50 million tons between 2010 and 2020. According to He et al. (2019), this program, called the Hundred Billion Plan (100 billion Jin equals 50 million tons), involved large-scale investments in irrigation and land improvements, as well as financial support for grain producers. Meanwhile, in 2013, the government issued an official document encouraging farmers in the western region to boost horticultural production to reduce rural income disparities between regions.[6] These situations suggest that while farmers in some provinces have gained economic benefits from crop diversification, those in others have limited access to such an opportunity.

2.2. *Agricultural production and productivity by region during 1984–2020*

China's central government divides the territory of mainland China into three regions—the eastern, central, and western regions—based on economic development and geographical location. This classification has been adopted by many scholars who analyze the interregional difference in agricultural production (Gong, 2020), and has also been followed in this study (Table 3).[7] Furthermore, we divide the period for the analysis into two, 1984–2000 and 2001–2020, considering the changes in agricultural production structure and interregional disparities over time. As shown below, the agricultural land-labor ratio increased marginally during 1984–2000, but it rose significantly during 2001–2020, contributing to an increase in agricultural labor productivity. In addition, the eastern region's share of agricultural output value peaked in approximately 2000 and declined thereafter, while the western region's share began to increase from the mid-2000 s.

Table 1 presents rural people's economic status in 2020, the period average of agricultural production and productivity, and their growth rate during the period concerned. The upper part of the table shows that, of the three regions, the average per capita disposable income of rural households (AIRHs) in the eastern region is among the highest, followed by the central region, with the western region being among the lowest. The ratio of wage income to the AIRHs varies greatly among regions, with the regional ranking being the same as for the AIRHs. The western region has the highest value of the rural population share and primary industry's gross output value share, suggesting that the region's urbanization and industry-led economic development lag far behind those of other regions.

This study divides farm products or production activities into three categories: sector 1 is grain, including rice, wheat, maize, beans, and tubers; sector 2 is cash crops, such as cotton, fiber crops, sugar crops, tobacco, and tea; and sector 3 is vegetables and fruits. Table 1 shows that the period average of sector 1′s production share in the total was 55.4% during 1984–2000, whereas it dropped to 36.8% during 2001–2020 (the shares are calculated based on weight). Similarly, sector 1′s shares in the eastern and western regions decreased by more than 20% points during the two periods, reaching 26.0% and 36.2% during 2001–2020, respectively. However, the comparable figure in the central region remained at 50.4%, reflecting the abovementioned government directive to promote grain production in this region.

The table summarizes the period average values of labor productivity (Y/L: ton/person), land productivity (Y/A: ton/ha), and the land-labor ratio (A/L: ha-person) for 1984–2000 and 2001–2020.[8] The value of Y/L is the highest in the eastern region, which is upheld by a large value of Y/A. The western region has the lowest value of Y/L throughout the entire period concerned. The value of A/L, considered a proxy for the average farm size of producers, is among the largest for the central region. This appears natural because grain production adopts land-use technology, and the extent to which this region specializes in grain production is relatively high. Meanwhile, the western region has the

[4] To boost grain production, China's central government introduced the producer subsidy program in 2004, the minimum procurement prices program for rice and wheat from 2004 to 2006, and the temporary stockpiling policy program for maize and soybeans from 2007 to 2008. Shortly after the implementation of these programs, the trend of decreasing grain-sown area was reversed dramatically (Yi et al., 2015).

[5] In China, the terms of trade for horticultural products have improved significantly over the period (Li and Ito, 2023), which is thought to have kept the profit margins of vegetables and fruits higher than those of cereals and cash crops.

[6] The western region's share of vegetable and fruit production in total rose from 14.0% in 2001 to 25.4% in 2020.

[7] For the data from 1984 to 2000, Chongqing and Sichuan Provinces, and Hainan and Guangdong Provinces are integrated in this study.

[8] Subsection 3.3 provides an explanation for how agricultural labor is estimated. Land productivity is measured by output divided by sown area.

lowest value of A/L throughout the period, indicating that agricultural labor is abundantly supplied relative to farmland.

This study calculates an annual compound growth rate (α_1) in the variables of interest (x_t) by estimating the following equation: $\ln x_t = \alpha_0 + \alpha_1 t + \varepsilon$, where t and ε denote the time variable and error term, respectively. Table 1 indicates that for the period 1984–2000, agriculture in the three regions achieved nearly equal growth rates in terms of the value and weight of production. Meanwhile, during 2001–2020, the growth rate of the real agricultural output value was uneven interregionally, with 3.0%, 4.3%, and 6.2% in the eastern, central, and western regions, respectively. A similar tendency can be seen in the growth rate of agricultural production on a weight basis. Notably, sector 3 in the western region grew more rapidly than in other regions during 2001–2020, which is considered to reflect the central government's initiative of promoting horticulture in this region. During 1984–2000, Y/L in the eastern region grew faster than that in the other two regions. However, from 2001 to 2020, the region's dominance faded, with the Y/L growth in the central and western regions outpacing the eastern region. In addition, during 1984–2000, an increase in Y/A is the main contributor to a rise in Y/L across the country, whereas during 2001–2020, an increase in A/L accounted for more than half of a rise in Y/L.

3. Methodology and data

3.1. The stochastic meta-frontier output distance function

To empirically examine the interregional and intertemporal productivity differences in China's agriculture, we employ a stochastic *meta*-frontier output distance function approach developed by scholars such as Battese et al. (2004), O'Donnell et al. (2008), and Huang et al. (2014). Let $Y^k_{1,it} = f^k_t(\boldsymbol{Y}^k_{(-1),it}, \boldsymbol{X}^k_{it})\xi^k_{it}\exp(v^k_{it})$ be the stochastic frontier output distance function (SFODF) of province i in the region k at year t, where $\boldsymbol{X}^k_{it}$ and $Y^k_{1,it}$ denote respectively a vector of input and a scalar of output, and $\boldsymbol{Y}^k_{(-1),it} = [Y^k_{2,it}, \cdots, Y^k_{m,it}]$. Furthermore, v^k_{it} and ξ^k_{it} represent random shock and the level of technical efficiency, respectively. It is assumed that v^k_{it} is independent and identically distributed (i.i.d.), with a mean of zero and variance of σ^{k2}_v. Meanwhile, it is assumed that $0 < \xi^k_{it} \leqslant 1$, implying that technical efficiency is strictly positive and equal to one or less.

Taking the natural logarithm of the above-defined SFODF, we have

$$\ln Y^k_{it} = \ln f^k_t(\boldsymbol{Y}^k_{(-1),it}, \boldsymbol{X}^k_{it}) - u^k_{it} + v^k_{it}$$

where $u^k_{it} = -\ln\xi^k_{it}$. From $0 < \xi^k_{it} \leqslant 1$, $u^k_{it} \geqslant 0$. The terms u^k_{it} are i.i.d. with $N^+(\mu^k_t, \sigma^{k2}_u)$. The two components of u and v are assumed to be distributed independently of one another, that is, $\sigma_{uv} = 0$. In this study, estimating k region specific SFODF is referred to as the first-stage estimation. The technical efficiency of province i in year t is given by

$$\mathrm{TE}^k_{it} = \frac{Y^k_{it}}{f^k_t(\boldsymbol{Y}^k_{(-1),it}, \boldsymbol{X}^k_{it})\exp(v^k_{it})} = \exp(-u^k_{it})$$

If $\mathrm{TE}^k_{it} = 1$, the province is performing its activities on the region-specific frontier of the production possibility set. If $0 < \mathrm{TE}^k_{it} < 1$, the province does not make the most of the input given the technology embodied in the frontier function.

Technical efficiency can be associated with a set of within-region province-specific exogenous variables $\boldsymbol{Z}^k_{it}$. It is usually assumed that the inefficiency term is linearly expressed as

$$-\mathrm{TE}^k_{it} = \delta + \boldsymbol{Z}^k_{it}\boldsymbol{\delta} + \varepsilon^k_{it} \tag{1}$$

To obtain consistent and unbiased estimators, we must estimate the production functions and inefficiency equations simultaneously (Battese and Coelli, 1995).[9]

The predicted value of Y^k_{it} on the region-specific frontier is given by

$$\widehat{Y}^k_{it} = f^k_t(\boldsymbol{Y}^k_{(-1),it}, \boldsymbol{X}^k_{it}) \equiv f^k_t(\cdot)$$

The *meta*-frontier envelops all individual regions' frontiers, and unlike the deterministic *meta*-frontier, it enjoys stochastic properties and accommodates idiosyncratic shock (Huang et al., 2014; Owusu and Bravo-Ureta, 2022). Namely, the common underlying *meta*-frontier production function, $g_t(\boldsymbol{Y}^k_{(-1),it}, \boldsymbol{X}^k_{it}) \equiv g_t(\cdot)$, for all provinces at the year of t is defined as

$$f^k_t(\cdot) = g_t(\cdot)\psi^k_{it} = g_t(\cdot)\exp(-w^k_{it})$$

where $w^k_{it} \geqslant 0$ $(0 < \psi^k_{it} \leqslant 1)$. Estimating the *meta*-SFODF is referred to as the second-stage estimation. Evidently, we have $g_t(\cdot) \geqslant f^k_t(\cdot)$, and the ratio of the k-th group's production frontier to the *meta*-frontier is defined as the technology gap ratio (TGR),

$$\mathrm{TGR}^k_{it} = \frac{f^k_t(\cdot)}{g_t(\cdot)} = \exp(-w^k_{it}) = \psi^k_{it}$$

As explained by Huang et al. (2014), the ratio of Y^k_{it} to $g_t(\cdot)$ is given by

$$\frac{Y^k_{it}}{g_t(\cdot)} = \frac{f^k_t(\cdot)}{g_t(\cdot)} \cdot \frac{Y^k_{it}}{f^k_t(\cdot)\exp(v^k_{it})} \cdot \exp(v^k_{it}) = \mathrm{TGR}^k_{it} \times \mathrm{TE}^k_{it} \times \exp(v^k_{it})$$

By accounting for the random noise component, the decomposition of this equation can be expressed alternatively as (Huang et al., 2014),

$$\mathrm{MTE}^k_{it} \equiv \frac{Y^k_{it}}{g_t(\cdot)\exp(v^k_{it})} = \mathrm{TGR}^k_{it} \times \mathrm{TE}^k_{it} \tag{2}$$

where MTE^k_{it} measures the province's technical efficiency with respect to the *meta*-frontier production function.

3.2. Specification of SFODF

We use a SFODF with multiple inputs and multiple outputs for the estimation of the interregional, intertemporal productivity differences in agriculture. An alternative model is a standard stochastic frontier production function (SSFPF), with the dependent variable being measured by real agricultural output value. We opt for the SFODF because the SSFPF with single-output cannot distinguish the difference in productivity increases that arise from total factor productivity growth and changes in the production mix[10].

Based on Brümmer et al. (2006), Coelli and Perelman (2000), we assume the following equation:

$$\ln Y_{1t} = -\ln D_O(\boldsymbol{X}_t, 1, \boldsymbol{Y}_t/Y_{1t}) + \ln D_{O\,t} = -\ln D_O(\boldsymbol{X}_t, \boldsymbol{Y}^*_t) + \ln D_{O\,t}$$

where the $\boldsymbol{X}_t$ and $\boldsymbol{Y}_t$ denote vectors of input and output at time t, respectively, and $\boldsymbol{Y}^*_t = \boldsymbol{Y}_t/Y_{1t}$. The function $D_O(\boldsymbol{X}_t, \boldsymbol{Y}^*_t)$ denotes the output distance function at t. Since we have $0 < D_{O\,t} \leqslant 1$, $-u_t = \ln D_{O\,t}$ is negative, with the maximum value equal to zero. The term $-u_t$ repre-

[9] It can be assumed that the variables $\boldsymbol{Z}$ in equation (1) not only influence technical efficiency but also affect output indirectly by shifting the production frontier (Kumbhakar and Lien, 2010). However, following the view of Giannakas et al. (2001) that the parameters included in equation (1) should capture relevant information that is omitted from the specification of the SFODF, we decided not to allow overlapping explanatory variables in equations (1) and the SFODF.

[10] Wiech et al. (2020) claim that the conventional approach of TFP yields valid measurement of productivity changes only if there is one output or the output mix is static over time. To remove bias stemming from changes in production mix, we adopt the SFODF approach, which explicitly incorporates multiple output production technology.

sents the inefficiency element with a one-sided disturbance; the closer the value of $D_{O\ t}$ is to unity, the more technically efficient the farmers' choices are. Thus, we have,

$$\ln Y_{1t} = -\ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t) - u_t \tag{3}$$

The estimated indicators, such as MTE, TGR, TE, TFP growth rate, and others, are completely independent of how the three sectors' output (Y_{1t}, Y_{2t}^*, Y_{3t}^*) are allocated in equation (3). By specifying $\ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t)$ in equation (3) as the *trans*-log form, we express the SFODF as:

$$\begin{aligned}-\ln Y_{1it} = {} & \alpha_0 + \sum_k \alpha_k \ln X_{kit} + \sum_m \beta_m \ln Y_{mit}^* + \frac{1}{2}\sum_k \sum_l \alpha_{kl} \ln X_{kit} \ln X_{lit} \\ & + \sum_k \sum_m \chi_{km} \ln X_{kit} \ln Y_{mit}^* + \sum_l \alpha_{lt} \ln X_{lit} \ln t + \frac{1}{2}\sum_m \sum_n \beta_{mn} \ln Y_{mit}^* \ln Y_{nit}^* \\ & + \sum_n \beta_{nt} \ln Y_{nit}^* \ln t + \sum_i \gamma_i (\text{year dummy}) + u_{it} + v_{it}\end{aligned} \tag{4}$$

All the Greek letters are parameters to be estimated. To capture biased technological change, we add cross terms of the time variable (t) and the input and output variables in equation (4). Meanwhile, neutral technological change is captured by the year dummy variables. Technical efficiency can be calculated as $\text{TE}_{it} = \exp(-u_{it})$. The parameters in equation (4) have properties of $\alpha_{kl} = \alpha_{lk}$ and $\beta_{mn} = \beta_{nm}$ from the symmetric conditions.

Given the estimators, the elasticity of scale is given by:

$$\eta = \sum_k \frac{\partial \ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t)}{\partial \ln X_{kt}} = -\sum_k \frac{\partial \ln Y_{1t}}{\partial \ln X_{kt}} = \sum_k \eta_{kt}$$

The production technology exhibits constant returns to scale when $\eta = 1$. If $\eta > (<)\ 1$, the technology exhibits increasing (decreasing) returns to scale. The monotonicity condition of the SFODF requires both $\partial \ln Y_{1t} / \partial \ln Y_{mt}^* > 0$ and $\partial \ln Y_{1t} / \partial \ln X_{lt} < 0$, which are reduced to $\beta_m > 0$ and $\alpha_l < 0$ at the mean values of the variables, respectively.

This study estimates the growth rate of total factor productivity (TFP), which is a comprehensive indicator of productivity growth and economic performance; it is given by

$$\frac{d\ln \text{TFP}}{dt} = \sum_{m=1}^{M} \widetilde{\omega}_{mt} \frac{d\ln Y_{mt}}{dt} - \sum_{n=1}^{N} \omega_{nt} \frac{d\ln X_{nt}}{dt}$$

where

$$\widetilde{\omega}_{mt} = \frac{\partial \ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t)}{\partial \ln Y_{mt}}$$

and

$$\omega_{nt} = \frac{\partial \ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t)/\partial \ln X_{nt}}{\sum_{k=1}^{N} \partial \ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t)/\partial \ln X_{kt}}$$

The growth rate of TFP can be decomposed into the following three components: technical change (TC), change in technical efficiency (ΔTE), and the contribution of scale economies (SE). (See Feng and Serletis (2010) for rigorous proof and Aguiar et al. (2017) for its empirical applications.) That is,

$$\frac{d\ln \text{TFP}}{dt} = \text{TC} + \Delta\text{TE} + \text{SE} \tag{5}$$

where

$$\text{TC} = -\frac{\partial \ln D_O(\boldsymbol{X}_t,\ \boldsymbol{Y}_t^*,\ t)}{\partial t} = \frac{\partial \ln Y_1}{\partial t}$$

$$\Delta\text{TE} = \frac{\partial \ln \text{TE}_{it}^k}{\partial t}$$

$$\text{SE} = \left(\frac{\eta - 1}{\eta}\right) \sum_k \left(-\frac{\eta_k}{\eta}\right) \frac{d\ln X_{kt}}{dt}$$

The scale effect (SE) has a positive effect on the growth rate of TFP if $\eta > 1$ and the aggregated input growth rate is positive, or in the case of input contraction under $\eta < 1$ (Aguiar et al., 2017). Meanwhile, as long as the production technology exhibits constant returns to scale ($\eta = 1$), the SE equals zero, implying that the TFP growth rate consists of a primal measure of the rate of technical change and the change in technical efficiency.

3.3. Data

This study draws on province-level data from 1984 to 2020 to estimate the SFODF. The major data sources are the Provincial Statistical Yearbook (PSY) published annually by the National Bureau of Statistics of China. There is a small subset of missing data in the period 1984–2000, which are filled using an interpolation method. Table A1 presents descriptive statistics of the variables used for the estimation of the SFODF and equation (1). Output is measured by weight (in a million tons) for sectors 1–3. The third Agricultural Census in 2016 revealed that the PSY overestimated horticultural production quantity between 2002 and 2016. Thus, this study corrects sector 3′s production quantity using production data compiled by the Food and Agriculture Organization of the United Nations (FAOSTAT). See Fig. A1 for the corrected statistics. In addition, to check robustness, we estimate in this study the SSFPF using data on agricultural output value at constant prices. To obtain data on real output value, we employ the distinct agricultural product prices as deflators for each province.

Factor inputs of the SFODF include fertilizer (*fer*), farm labor (*lab*), farm machinery (*cap*), and sown area (*lad*). Fertilizer is measured by the total chemical fertilizer consumption that is converted to net ingredients (million tons). Farm labor is measured by the total number of workers engaged in crop farming (million persons), which is not obtained directly from the PSY. Thus, we first compute the ratio of the gross output value of agriculture to that of the primary industry at the provincial level for each year and then estimate farm labor by multiplying the ratio by the total labor force in the primary industry (Yao et al., 2001). Farm machinery is measured by the total power of agricultural machines (million kilowatts) used for agricultural production. Farmland is measured by the total sown area (million ha). A *trans*-log function is a second-order Taylor-series approximation centered at zero. Therefore, prior to the SFODF estimation, all the respective output and input variables are normalized such that $\ln\overline{X} = \ln\overline{Y} = \ln\overline{t} = 0$.

There exists no formal procedure to follow when deciding which variables should be included in the inefficiency equation (Tian and Wan, 2000). Furthermore, the variables used for the inefficiency equation in the first-stage estimation must differ from those used for the second-stage estimation (Huang et al., 2014). This study uses two variables for the first-stage estimation: the irrigation rate (*irri*) and the agricultural land area damaged by natural disasters divided by the sown area (*dam*). Meanwhile, the regional dummy variables and time trend are used as regressors for the inefficiency equation in the second stage.

4. Estimation results

4.1. SFODF estimators

Before estimating the SFODF, we verify the stationarity of the variables of interest, including the regressand. A Fisher-type unit root test strongly rejects the null hypothesis that all panels contain unit roots in favor of the alternative that at least one panel is a stationary process. Additionally, this study tests the null hypothesis of no cointegration for the SFODF equation. The null hypothesis is rejected at the 1% significance level, suggesting that the regressors in the panel dataset are

Table 2
Estimation results of the SFODF.

	Combined (1984–2020)		Separated (1984–2000)		Separated (2001–2020)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Equation (4)						
ln V	−0.242***	(0.015)	−0.179***	(0.025)	−0.249***	(0.025)
ln L	−0.083***	(0.015)	−0.166***	(0.031)	−0.090***	(0.020)
ln K	−0.053***	(0.015)	0.004	(0.043)	0.012	(0.018)
ln A	−0.687***	(0.026)	−0.672***	(0.049)	−0.672***	(0.038)
ln Y_2	0.095***	(0.006)	0.098***	(0.013)	0.096***	(0.009)
ln Y_3	0.165***	(0.009)	0.091***	(0.014)	0.216***	(0.014)
ln V*ln L	0.036**	(0.017)	0.062**	(0.027)	−0.021	(0.046)
ln V*ln K	0.035*	(0.021)	0.091***	(0.034)	−0.012	(0.045)
ln V*ln A	−0.064**	(0.026)	−0.032	(0.041)	−0.199***	(0.058)
ln L*ln K	−0.055**	(0.023)	−0.029	(0.038)	0.040	(0.028)
ln L*ln A	0.331***	(0.036)	0.354***	(0.049)	0.051	(0.066)
ln K*ln A	0.135***	(0.035)	−0.088*	(0.052)	−0.051	(0.050)
0.5*ln V*ln V	−0.037**	(0.018)	−0.118***	(0.026)	0.172***	(0.065)
0.5*ln L*ln L	−0.264***	(0.032)	−0.342***	(0.052)	−0.035	(0.059)
0.5*ln K*ln K	−0.140***	(0.030)	−0.062	(0.075)	0.024	(0.041)
0.5*ln A*ln A	−0.315***	(0.064)	−0.142**	(0.068)	0.278**	(0.112)
ln V*ln Y_2	−0.012	(0.008)	0.029**	(0.013)	0.013	(0.018)
ln L*ln Y_2	0.027**	(0.011)	−0.005	(0.026)	0.010	(0.015)
ln K*ln Y_2	0.017*	(0.010)	0.081***	(0.027)	−0.031*	(0.013)
ln A*ln Y_2	−0.053***	(0.014)	−0.104***	(0.037)	−0.053***	(0.018)
ln V*ln Y_3	−0.005	(0.012)	−0.005	(0.021)	−0.023	(0.025)
ln L*ln Y_3	0.046***	(0.013)	0.057**	(0.028)	0.010	(0.025)
ln K*ln Y_3	0.043***	(0.013)	0.007	(0.028)	0.002	(0.023)
ln A*ln Y_3	−0.077***	(0.018)	0.031	(0.042)	0.004	(0.038)
ln V*ln t	0.006***	(0.001)	0.016***	(0.003)	0.005**	(0.002)
ln L*ln t	−0.001	(0.001)	0.004	(0.004)	0.002	(0.002)
ln K*ln t	−0.003*	(0.002)	−0.008*	(0.005)	−0.004*	(0.002)
ln A*ln t	−0.003	(0.002)	−0.010**	(0.005)	−0.006*	(0.003)
ln Y_2*ln Y_3	−0.000	(0.006)	−0.019*	(0.011)	−0.016*	(0.009)
0.5*ln Y_2*ln Y_2	−0.003	(0.005)	0.005	(0.013)	−0.002	(0.006)
0.5*ln Y_3*ln Y_3	0.070***	(0.010)	0.015	(0.016)	0.064***	(0.020)
ln Y_2*ln t	0.001**	(0.001)	−0.005***	(0.002)	0.001	(0.001)
ln Y_3*ln t	−0.002*	(0.001)	−0.001	(0.002)	−0.001	(0.002)
Eastern dummy	0.270***	(0.036)	0.372***	(0.075)	0.153***	(0.048)
Central dummy	0.140***	(0.043)	0.341***	(0.074)	0.117**	(0.052)
Year dummy	YES		YES		YES	
Equation (1)						
irri	−1.095***	(0.194)	−2.218***	(0.627)	−1.579***	(0.480)
dam	1.830***	(0.220)	1.513***	(0.197)	1.417***	(0.183)
Number of observations	1112		492		620	
Log-likelihood	1421.1		622.9		969.8	
Mean technical efficiency	0.767		0.662		0.831	

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables of V, L, K, A, and t denote fertilizer, farm labor, farm machinery, sown area, and time, respectively. The variables of equation (1), *irri* and *dam*, denote the irrigation rate and agricultural land area damaged by natural disasters divided by the sown area, respectively.

cointegrated in the long run. Tables A2 and A3 show these test results.

To remove potential bias stemming from time-invariant unobservables, we employ a fixed effects model for the estimation of equations (4) and (1).[11] Table 2 presents the estimation results of the SFODF for the combined (1984–2020) and two separated (1984–2000 and 2001–2020) periods.[12] We test a null hypothesis that SFODF estimators do not differ between the two separated periods, which is verified by a likelihood-ratio test, also known as the Chow test; the likelihood-ratio statistics are defined as $\lambda = -2[\ln L(H_0) - \ln L(H_1)]$, where $\ln L(H_0)$ is the value of the log likelihood for the combined-period estimation, while $\ln L(H_1)$ is the sum of the values of the log likelihood for the two separated-period estimations. The statistical value of λ equals 343.26 (Prob $>$ chi2 $=$ 0.0000), suggesting that the null hypothesis can be rejected.[13]

The coefficients of the "eastern dummy" and "central dummy" variables for the combined estimation shown in Table 2 are 0.270 and 0.140, respectively, and are significant at the 1% level. It implies that the agricultural productivity of the eastern and central regions is 1.31 and 1.15 times higher, respectively, than that in the western region. There is also a significant difference in productivity between the eastern and central regions (p-value: 0.001). The coefficients of the "eastern dummy" and "central dummy" for 1984–2000 are 0.372 and 0.341, respectively, whereas the comparable figures for 2001–2020 are 0.153 and 0.117, respectively.[14] These findings suggest that the interregional differences in agricultural productivity between the eastern and central

[11] We test a null hypothesis regarding the exogeneity of the *irri* variable, using the ratio of fiscal expenditures for agriculture to the sown area as an instrument. The null hypothesis regarding the exogeneity of *irri* cannot be rejected for some SFODFs, and can be for others. It turned out, however, that the estimated values of indicators, such as MTE, TGR, TE, TFP growth rate, and others, have no large differences, regardless of the exogenous or endogenous models.

[12] To estimate the SFODF, we use the Stata command of "xtsfkk" developed by Karakaplan (2017).

[13] Another statistical test confirms the appropriateness of a stochastic model in that the ratio of σ_u^2 to the total variance $(\sigma_u^2 + \sigma_v^2)$ is significantly different from zero.

[14] There is no significant difference between 0.372 and 0.341 or 0.153 and 0.117.

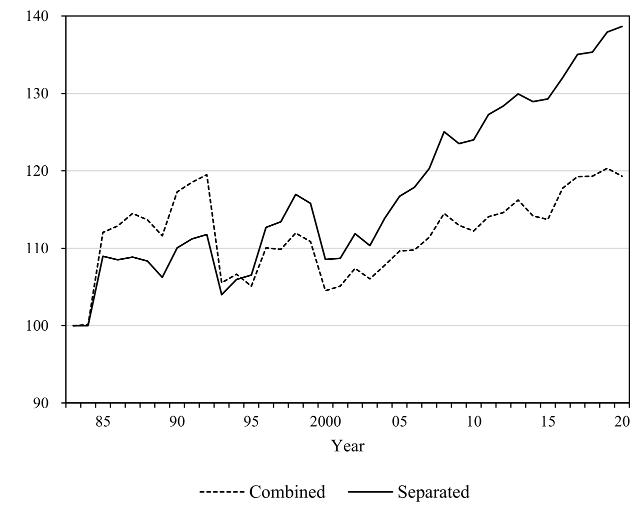

Fig. 2. Technical indexes of crop production in China (1983 = 100). Note: The "combined" index is calculated from the SFODF estimators for the 1984–2020 period, whereas the "separated" index is calculated from the two distinct SFODF estimators for 1984–2000 and 2001–2020 periods.

regions and the western region have narrowed substantially over time. This issue will be discussed in more detail below.

Table 2 reveals that the coefficient of the irrigation rate (*irri*) is negative and highly significant for the combined and two separated estimation results, suggesting that an increase in the irrigation rate helps improve the technical efficiency. In contrast, the coefficient of the land area damaged by natural disasters divided by the sown area (*dam*) is positive and significant, suggesting that the *dam* is negatively associated with technical efficiency. These results meet our prior expectation. The bottom of Table 2 presents the mean value of technical efficiency. The efficiency score for "combined" is 0.767, meaning that the average production could have been increased by approximately 23% if it had become technically efficient. Meanwhile, the average efficiency scores for the two "separated" are 0.662 and 0.831, suggesting an efficiency improvement between the periods 1984–2000 and 2001–2020.

Fig. 2 illustrates the technical index with 1983 as 100, which is the cumulative annual growth rate of technical change. The "combined" index is calculated from the SFODF estimators for the 1984–2020 period, whereas the "separated" index is calculated from the two distinct SFODF estimators (Table 2). The "separated" index is created by linking the two indexes in 2000. The annual compound rate of technological progress during 1984–2020, based on the "combined" index, is 0.21%. Meanwhile, the comparable rates for 1984–2000 and 2001–2020, based on the "separated" indexes, are 0.52% and 1.21%, respectively. It is reasonable to consider that the "separated" index is more preferable to the "combined" index because the null hypothesis regarding the no-difference in the SFODF estimators between the two different periods is statistically rejected, as described previously. Another reason is that the rate of technological progress based on the "combined" index is extremely low compared to estimates from preceding studies (Fuglie, 2018; Jin et al., 2010; Sheng et al., 2020). It shows that China's agricultural technology grew much faster during 2001–2020 than during 1984–2000, which will be discussed at length in subsection 4.3.

4.2. Interregional and intertemporal differences in the MTE, TGR, and TE

This subsection first tests the null hypothesis that there are no differences in the SDODF estimators among regions, drawing on the same method adopted in Subsection 4.1. The likelihood-ratio statistical values

Table 3
Average MTE, TGR, and TE by province for 1984–2000 and 2020–2020.

Province	Region	MTE		TGR		TE	
		1984–2000	2001–2020	1984–2000	2001–2020	1984–2000	2001–2020
Beijing	E	0.931	0.955	0.941	0.966	0.990	0.988
Tianjin	E	0.887	0.871	0.974	0.988	0.911	0.881
Hebei	E	0.552	0.769	0.815	0.905	0.678	0.850
Liaoning	E	0.740	0.897	0.954	0.911	0.776	0.985
Shanghai	E	0.866	0.857	0.889	0.871	0.974	0.984
Jiangsu	E	0.733	0.777	0.837	0.901	0.876	0.862
Zhejiang	E	0.715	0.768	0.774	0.921	0.924	0.835
Fujian	E	0.716	0.699	0.820	0.826	0.873	0.847
Shandong	E	0.684	0.840	0.790	0.914	0.866	0.919
Guangdong	E	0.795	0.790	0.809	0.819	0.983	0.965
Guangxi	E	0.635	0.797	0.855	0.867	0.742	0.920
Hainan	E	–	0.713	–	0.877	–	0.813
Shanxi	C	0.498	0.542	0.781	0.892	0.638	0.608
Inner Mongolia	C	0.497	0.661	0.744	0.883	0.667	0.749
Jilin	C	0.807	0.830	0.993	0.995	0.813	0.834
Heilongjiang	C	0.631	0.753	0.747	0.761	0.844	0.989
Anhui	C	0.590	0.623	0.839	0.864	0.703	0.722
Jiangxi	C	0.639	0.714	0.860	0.903	0.743	0.791
Henan	C	0.596	0.725	0.986	0.989	0.604	0.734
Hubei	C	0.678	0.637	0.856	0.805	0.792	0.792
Hunan	C	0.740	0.712	0.846	0.751	0.875	0.948
Chongqing	W	–	0.635	–	0.971	–	0.654
Sichuan	W	0.809	0.728	0.896	0.865	0.903	0.842
Guizhou	W	0.438	0.516	0.503	0.952	0.870	0.542
Yunnan	W	0.543	0.632	0.554	0.683	0.980	0.925
Tibet	W	0.452	0.843	0.553	0.854	0.816	0.988
Shaanxi	W	0.453	0.505	0.649	0.983	0.698	0.514
Gansu	W	0.438	0.539	0.620	0.965	0.707	0.558
Qinghai	W	0.456	0.501	0.493	0.700	0.924	0.717
Ningxia	W	0.496	0.583	0.502	0.957	0.988	0.608
Xinjiang	W	0.570	0.614	0.585	0.686	0.975	0.896

Note: E, C, and W denote the eastern, central, and western regions, respectively. MTE: technical efficiency based on the stochastic *meta*-frontier output distance function; TGR: the technology gap ratio; TE: the region-specific technical efficiency.

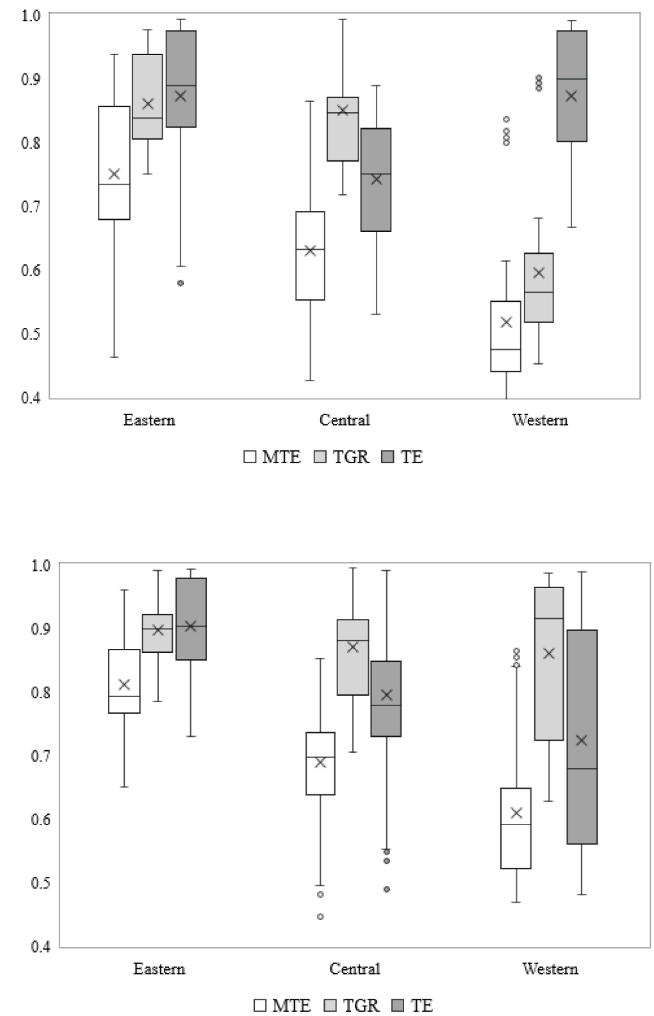

Fig. 3. Estimated MTE, TGR, and TE by region (1984–2000: above; 2001–2020: below). Note: MTE: technical efficiency based on the stochastic *meta*-frontier output distance function; TGR: the technology gap ratio; TE: the region-specific technicaefficiency.

(λ) for 1984–2000 and 2001–2020 are 343.49 (Prob $>$ chi2 $=$ 0.0000) and 438.48 (Prob $>$ chi2 $=$ 0.0000), respectively, suggesting that the null hypothesis can be rejected for both periods. Thus, a "traditional stochastic model" using pooled data is inappropriate for comparing TEs across provinces. From the region-specific SFODF estimation, we obtain the predicted value of Y_{it}^{k}, which is used as a regressand for the *meta*-SFODF estimation. The estimation results of time- and regional-specific SFODFs and *meta*-SFODF are available on request.

Table 4
Decomposition of TFP growth (%).

		Output growth	TFP	TC	ΔTE	SE
1984–2000	National	4.53	0.57	0.52	0.01	0.03
	Eastern	4.80	1.41	1.36	0.00	0.05
	Central	4.32	−0.61	−0.22	0.15	−0.54
	Western	4.26	0.03	−0.51	0.03	0.51
2001–2020	National	2.80	1.47	1.21	0.25	0.01
	Eastern	1.94	0.84	0.68	0.14	0.02
	Central	3.19	1.21	0.80	0.43	−0.02
	Western	3.98	1.58	1.33	0.16	0.10

Note: TFP: total factor productivity; TC: technical change; ΔTE: technical efficiency change; SE: scale effect.

Table 3 presents the calculation results of equation (2) for each province. The values in the table are the period average for 1984–2000 and 2001–2020. Generally, the eastern provinces have high MTE scores, as typified by Beijing, while western provinces have relatively low scores, consistent with Gong's (2018) study. The TGR score in most, if not all, provinces improved significantly between the periods 1984–2000 and 2001–2020. This result signifies that the region-specific frontiers have approached the *meta*-frontier function over time. As is evident from the argument in section 3, a high score of the TE does not necessarily mean that the province is performing well in agriculture. The further the region-specific frontier function is from the *meta*-frontier—the smaller the TGR score—the larger the room exists for the province to improve technical efficiency.

Fig. 3 illustrates the three indicators of MTE, TGR, and TE with a box-and-whisker plot for the three regions (above: 1984–2000, below: 2001–2020). It clearly shows that for the two time periods, the eastern region recorded the highest MTE score, followed by the central region, with the western region being among the lowest. The pairwise mean comparison reveals that there are significant differences in the average MTE scores among the three regions in both periods.[15] A similar trend is witnessed for the TGR during 1984–2000, with the eastern region being among the highest and the western region being the lowest (no significant difference between the eastern and central regions). Meanwhile, the average score of the TE in the western region during 1984–2000 is 0.874, which favorably compares with that in the eastern region of 0.872, with no significant difference. It means that agriculture in western provinces is as efficient as that in eastern provinces in terms of the region-specific frontier function. However, the western region had a low TGR score during 1984–2000, indicating that it was far behind the central and eastern regions in terms of agricultural technology.

The period of 2001–2020 witnessed a drastic change in the TGR score in the western region; it rose to 0.862, which was not significantly different from the score in the central region (although there was a difference from the eastern region at the 5% significance level). An approach of the western region-specific frontier function to the *meta*-frontier function can be viewed as a desirable outcome from the viewpoint of reducing interregional disparities. However, in this process, the region-specific average TE in the western region has declined significantly. A scrutiny of Table 3 reveals that western provinces that improved their TGRs over time lowered their TE scores during the two periods. This finding implies that such provinces have succeeded in closing the distance between their province-specific frontier and the *meta*-frontier functions but failed to run agricultural production efficiently relative to their regional frontier. Boshrabadi et al. (2008) argue that region-specific technical efficiency is likely to improve by accommodating province-specific agricultural constraints. In the context of the present study, it can be attained by increasing the irrigation rate and mitigating damage from natural disasters.

4.3. Decomposition of TFP growth

As equation (5) indicates, the TFP growth rate is decomposed into three elements: technical change (TC), a change in technical efficiency (ΔTC), and scale effects (SE).[16] We compute the individual elements from the region-specific SFODF estimated separately for 1984–2000 and 2001–2020 and show the results in Table 4. From 1984 to 2000, the

[15] For the pairwise mean comparison, we use both the Bonferroni error correction method and Dunnet method.

[16] The TC is composed of the neutral technical change and biased technical change; the latter's contribution to the rate of TC is negligibly small. The estimation results of the SFODF (Table 2) show that technological change has been fertilizer- and labor-saving, and capital- and land-using over the last 40 years, while it has sector 2-reducing and sector 3-augmenting characteristic during 1984–2020. However, the biases have a large interregional difference.

Table 5
Robustness check: The average MTE, TGR, and TE.

		MTE		TGR		TE	
1984–2000	Eastern	0.658	(0.138)	0.860	(0.092)	0.770	(0.165)
	Central	0.520	(0.089)	0.650	(0.093)	0.801	(0.094)
	Western	0.449	(0.150)	0.509	(0.145)	0.877	(0.079)
2001–2020	Eastern	0.709	(0.125)	0.868	(0.088)	0.819	(0.126)
	Central	0.504	(0.104)	0.669	(0.133)	0.774	(0.178)
	Western	0.483	(0.124)	0.809	(0.125)	0.613	(0.186)

Note: The numbers in the parentheses are the standard deviations. MTE: technical efficiency based on the stochastic *meta*-frontier output distance function; TGR: the technology gap ratio; TE: the region-specific technical efficiency.

Table 6
Robustness check: Decomposition of TFP growth (%).

		Output growth	TFP	TC	ΔTE	SE
1984–2000	National	4.91	0.05	2.08	−0.10	−1.93
	Eastern	4.96	1.68	1.82	−0.01	−0.13
	Central	4.52	−0.57	1.43	−0.06	−1.93
	Western	5.51	0.00	−0.20	−0.21	0.42
2001–2020	National	4.19	2.26	2.37	0.04	−0.15
	Eastern	2.97	2.60	2.57	0.00	0.03
	Central	4.34	3.46	3.22	0.19	0.06
	Western	6.18	4.44	3.48	0.91	0.05

Note: TFP: total factor productivity; TC: technical change; ΔTE: technical efficiency change; SE: scale effect.

agricultural output at the national level increased at an annual rate of 4.53%, with the rate being almost the same across regions. Despite the relatively high output growth during this period, the contribution of TFP was very small, implying that input augmentation was the main driver of the increase in output. It is also worth noting that the central and western regions have negative TC, indicating the retrogression of agricultural technology.[17] Chen et al. (2008), who analyze the productivity of China's agricultural sector over the period 1990–2003, demonstrate that TFP grew in most provinces, but it has deteriorated in poor regions. Their arguments are consistent with the results in this study despite certain differences in the period for the analysis.

During the period 2001–2020, the agricultural output grew differently across regions, with the lowest in the eastern region (1.94%) and the highest in the western region (3.98%). More noteworthy is that TFP growth accounted for approximately 40% of the annual output growth for all regions, of which technical change was the largest contributor. It is consistent with other empirical studies focusing on Chinese agriculture (Chen et al., 2008; Diao et al., 2018; Shen et al., 2019). Furthermore, many scholarly studies conducted in various countries have corroborated that R&D makes a great contribution to agricultural productivity improvements, and similar arguments can be seen in Chinese agriculture (Fuglie, 2018; Pratt et al., 2009; Sheng et al., 2020). Huang and Yang (2017) argue that China's central government has invested heavily in agricultural R&D since the mid-2000s. OECD (2018) also shows that agricultural R&D expenditure in China was almost four times greater in 2013 than in 2000 in real terms. Thus, it is reasonable to consider that the government's strong commitment to scientific innovation in agriculture is largely responsible for a rise in technological progress between 2001 and 2020.

Furthermore, China's accession to WTO in 2001 and the resultant trade liberalization has also fostered China's ability to exploit the comparative advantage it had in markets for labor-intensive products such as vegetables and fruits (Liu and Revell, 2009; Martin, 2001). In particular, net vegetable exports more than tripled from 3.47 million tons to 10.51 million tons between 2001 and 2020.[18] It may be related to the fact that the western region, whose production growth of horticulture (sector 3) was among the highest during 2001–2020 (Table 1), had the highest growth rates of TFP and TC and gained a high TGR score in this period. Diao et al. (2018) assert that during 2000–2014, the TFP of China's crop production grew fastest in the western region, followed by the central region. Given that the western region lagged behind others in the 1980 s and 1990 s in terms of agricultural technology, these findings confirm the cross-regional productivity convergence over time. Wang et al. (2019) empirically examine whether the TFP of Chinese agriculture exhibits a tendency to converge among provinces during 1985–2013. Their results show clear evidence of "catch-up" effects that provinces with lower TFP levels grew much faster than those with higher TFP levels in the past.[19] The present study supports the claims of Diao et al. (2018) and Wang et al. (2019), mainly because agricultural technology in the western region has advanced the fastest, thus narrowing the technological gap between the regions.[20]

4.4. Robustness check

To check robustness, we estimate the region-specific and *meta*-frontier stochastic production functions with single-output and multiple-inputs (SSFPF) instead of multiple outputs and multiple inputs. The frontier function is specified in the *trans*-log form, with the output measured by the agricultural output value at constant prices. In line with the analysis in the present study, 31 provinces are divided into the three regions. As null hypotheses that the *trans*-log stochastic frontier functions do not differ between the two periods and among the three regions were rejected, we estimate the model for the two separate periods and each region. The estimation results of regional-specific and *meta*-frontier stochastic functions are available on request.

Table 5 presents the estimation results of the MTE, TGR, and TE. The pairwise comparisons revealed differences in these indicators at the conventional level of significance, except for the TE between the eastern and central regions during 1984–2000 and the MTE between the central and western regions during 2001–2020. Although the average values of MTE in this table are smaller than those in Fig. 3, the regional order for

[17] As the agricultural production in the western region exhibited increasing returns to scale, the scale effect (SE) is large enough to compensate the negative TC. The elasticity of scale in the other regions is not different from unity at the conventional level of significance.

[18] Net export quantity of fruits increased significantly until 2007, but has been negative since 2018. China's labor-intensive agricultural sector is anticipated to lose its international competitiveness in the near future due to an increase in the opportunity cost of farm labor.

[19] Wang et al. (2013) estimate agricultural TFP growth for 25 Chinese provinces over the 1985–2007 period. Their estimation result shows the tendency toward faster TFP growth in relatively well-off coastal regions, implying a widening regional inequality. However, this does not contradict our result because agricultural TFP in the western region has grown rapidly since the late 2000s.

[20] Gong's (2020) study, using panel data at the province, county and commodity level in China for 1978–2015, denied the convergence.

the scores is the same, with the eastern region being among the highest, whereas the western region being the lowest. Most noteworthy in this table is that the western region's TGR score increased significantly from 0.509 during 1984–2000 to 0.809 during 2001–2020, reaching a level comparable with that in the eastern region. Namely, the western region made remarkable progress in agricultural technology during the period 2001–2020, consistent with Fig. 3.

Table 6 summarizes the results of the decomposition analysis of the TFP growth rate. Similar to the results in Table 4, TFP contributes less to the output growth for all regions during 1984–2000. Meanwhile, from 2001 to 2020, the agricultural real output value in the western region grew at the fastest rate of 6.18%, which was followed by the central region (4.34%) and the eastern region (2.97%). The fact that TFP and TC grew fastest in the western region is the same as the result shown in Table 4. Furthermore, there is full agreement between Tables 4 and 6 in that TC is the largest contributor to TFP growth. Table 6 reveals that the TFP growth rate accounts for more than 70% of the output growth rate for all regions during the period 2001–2020, the value of which is larger than that in Table 4. It is probably because the productivity increase associated with an increased share of horticultural production due to the improved terms of trade is added to the original TFP growth rate, which is the sum of technological progress, ΔTC, and SE (equation (5)). Thus, we can conclude that the estimation results are robust except for the last point.

5. Discussion and policy implications

Rapid economic growth and urbanization, and drastic changes in people's eating habits, have threatened China's long-standing goal of maintaining grain self-sufficiency. In response to this challenge, China's central government decided in 2013 to partially relax its self-sufficiency targets for grain. Specifically, it took the lead in promoting horticultural production in the western region, whereas it restricted such crop diversification in other regions to maintain grain production at a certain level. Concurrently, the last few decades have witnessed a structural transformation in Chinese agriculture: an overall rise in the land-labor ratio and a decline in the economic advantage of the eastern region. This study empirically examined how the policy shifts interacted with the interregional and intertemporal productivity differences in Chinese agriculture. For this purpose, we employed a *meta*-frontier output distance function approach as an analytical tool, which has an advantage over a traditional frontier model in that it can identify the technological gap between the region-specific frontier and the *meta*-frontier functions.

We divided the periods for the analysis into 1984–2000 and 2001–2020, considering the potential structural change and regional differentiation in agriculture. The statistical test confirmed the intertemporal difference in the production technology. Most noteworthy in this regard is that input augmentation was the main contributor to agricultural output growth during 1984–2000, whereas TFP was the main driver of growth during 2001–2020. It lends strong support to the argument that Chinese crop production has recently transformed from resource-input-driven activity to one spurred by science and technology (Xu et al., 2017).

This empirical study also sheds light on agricultural backwardness in the western region and its catch-up process. In this context, distinguishing between intra- and interregional productivity disparities is of particular importance to accurately diagnose the cause of this problem. Our estimation result offers unambiguous evidence that a huge distance exists between the western-specific frontier and the *meta*-frontier functions during 1984–2000, suggesting that the western region fell far behind in terms of agricultural technology. Furthermore, the regional disparity worsened during this period. However, the recent two decades witnessed a drastic change; the western region succeeded in catching up with the central region in this respect, which does not contradict our finding that the western region made remarkable progress in agricultural technology during 2001–2020.

We cannot delve econometrically into the causal effect of recent policy shifts on interregional and intertemporal productivity differences. However, in the western region, horticulture has seen steady growth and TFP grew fastest across regions during 2001–2020. Intrinsically, China has a comparative advantage in growing labor-intensive crops, such as vegetables and fruits, which require much labor per unit of land, compared to grain production. Furthermore, in the western region, the agricultural labor force is abundantly supplied relative to farmland. Given these facts, farmers in this region were better able to gain higher economic returns from crop conversion into horticulture, for which they might have been all the more motivated to improve their regional-specific productivity. Meanwhile, farmers in the central region, who specialized more in grain production, were not able to improve their technical efficiency as much as those in the western region. It may be ascribed to the fact that China has already lost its international competitiveness in this crop sector. Nevertheless, further research should be devoted to examine the causality between policy shifts and the interregional productivity differences.

Funding source

Funding from the Japan Society for the Promotion of Science (21H02295) is greatly acknowledged.

CRediT authorship contribution statement

Junichi Ito: Conceptualization, Methodology, Investigation, Software, Writing – review & editing. **Xinyi Li:** Visualization, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

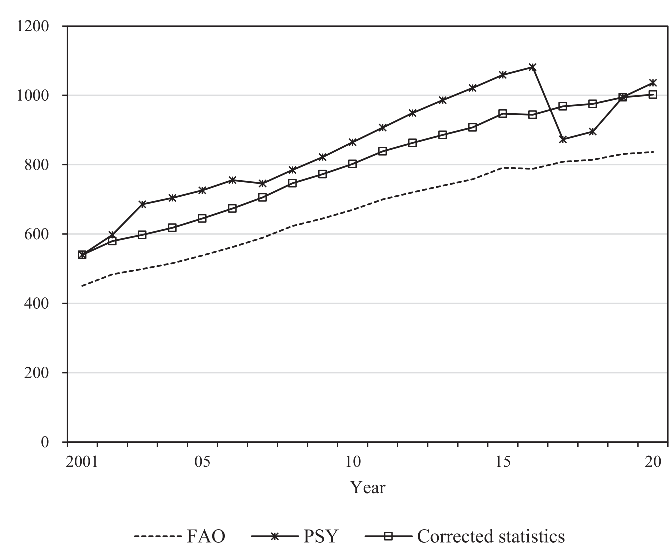

Fig. A1. Correction of horticultural production statistics (national total, million tons). Source: Provincial Statistical Yearbook, FAOSTAT. Note: We corrected the statistics by assuming that the annual growth rate of horticultural production calculated from FAOSTAT data is accurate. PSY: Provincial Statistical Yearbook.

Table A1
Variable descriptions and summary statistics.

Variables	Descriptions		Mean	SD
Y_1	Sector 1′s production by weight (million tons)	overall	16.86	13.94
		between		12.91
		within		5.63
Y_2	Sector 2′s production by weight (million tons)	overall	4.42	10.08
		between		8.77
		within		5.01
Y_3	Sector 3′s production by weight (million tons)	overall	18.33	21.71
		between		16.56
		within		14.12
-	The nominal agricultural output value (10 billion yuan)	overall	12.79	11.72
		between		9.14
		within		7.51
V	Chemical fertilizer consumption (million tons)	overall	1.35	1.26
		between		1.05
		within		0.72
L	Total numbr of workers engaged in crop production (million persons)	overall	5.56	4.73
		between		4.39
		within		1.90
K	Farm machinery measured by power (million kilowatt)	overall	20.72	23.06
		between		18.30
		within		14.25
A	Sown area (million ha)	overall	5.15	3.57
		between		3.53
		within		0.79
irri	Irrigation rate	overall	0.40	0.22
		between		0.17
		within		0.15
dam	The agricultural land area damaged by natural disasters divided by the sown area	overall	0.26	0.18
		between		0.08
		within		0.16

Source: Provincial Statistical Yearbook.
Note: Data for the real agricultural output value are available only for 2001–2020.

Table A2
Unit-root Fisher tests (*p*-values).

	Inverse chi-squared	Inverse normal	Inverse logit *t*	Modified inv. chi-squared
$\ln Y_1$	0.000	0.000	0.000	0.000
$\ln V$	0.000	0.000	0.000	0.000
$\ln L$	0.000	0.000	0.000	0.000
$\ln K$	0.001	0.002	0.003	0.000
$\ln A$	0.000	0.000	0.000	0.000
$\ln Y_2$	0.000	0.000	0.000	0.000
$\ln Y_3$	0.000	0.000	0.000	0.000

Note: A Fisher-type unit-root test was used, because it works well with an unbalanced panel.

Table A3
Cointegration tests).

	Statistic	*p*-value
Modified Dicky-Fuller *t*	−6.40	0.000
Dickey-Fuller *t*	−5.63	0.000
Augmented Dickey-Fuller t	−3.06	0.001
Unadjusted modified Dicky-Fuller *t*	−8.49	0.000
Unadjusted Dickey-Fuller *t*	−6.32	0.000

Note: A Kao test was used and all test statistics reject the null hypothesis of no cointegration, in favor of the variables being cointegrated in all panels.

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