

## Research Article

# Research of Total Factor Productivity and Agricultural Management Based on Malmquist-DEA Modeling

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Received 16 May 2021; Revised 4 June 2021; Accepted 25 June 2021; Published 2 July 2021

Academic Editor: Wen-Tsao Pan

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Based on the Malmquist-DEA Modeling and drawing on the data from 12 cities in Hubei, a central province of China, this paper measures the total factor productivity (TFP) of agricultural management as well as technological change (TC) and technical efficiency change (EC). The Cobb–Douglas (C-D) production function is adopted to empirically estimate the impacts of TFP and its constituent elements on the agricultural management and economic growth comprehensively and further study the effects on different regions in Hubei. The results demonstrate that TC grows at an annual average rate of 6.7% and drives agricultural TFP growth in Hubei. The decline in scale efficiency accounts for the drop of 1.1% of EC. The agricultural TFP growth rates among different regions vary remarkably but overall have a positive and significant effect on agricultural output. The research sheds light on the analysis of agricultural development of Hubei according to the findings based on Malmquist-DEA Modeling and provides practical implications for the future management.

## 1. Introduction

According to the report delivered at the 19th CPC National Congress held in 2017, efforts should be made for better quality, higher efficiency, and more robust drivers of China's economic growth through reform, and TFP needs to be raised. In neoclassical economics, economic growth is sourced from two parts: the growth of factors of production and the growth of TFP. TFP can be raised significantly if limited input factors are effectively used and allocated. Therefore, with limited resources given, improving TFP is the key to achieve high-quality development. TFP, as previous studies suggested, is a key indicator to measure the quality of economic growth in a country or region and is crucial for economic and social development [1]. If the conventional, unsustainable pattern of high input and excessive waste for high yield were to change to achieve quality agricultural development, the top priority would be to increase TFP and replace old growth drivers with new ones.

It is imperative for China's major agricultural provinces such as Hubei to achieve high-quality development and to

grow strong in agriculture by leveraging limited agricultural resources. A key to addressing the issue is to multiply the contribution of TFP to agricultural growth. Thus, this study starts from the measurement and decomposition of agricultural TFP in a new landscape and then introduces TFP and its decomposed elements to the C-D production function to analyze how input factors, such as TC, EC, capital, and labor, contribute to the growth of Hubei's agricultural economy. Meanwhile, this paper offers proposals on how to maintain a stable and high-quality agricultural economy through analysis on regional disparity within Hubei province.

## 2. Literature Review

In the 1950s, American economist Robert Merton Solow built the aggregate production function and growth model that exhibit constant returns to scale (CRS) and further proposed the concept of TFP, believing that its increase was attributed to TC [2]. This has laid a solid theoretical foundation for research on TFP.

Generally, there are two types of approaches to measuring agricultural TFP: frontier and nonfrontier. A majority of research efforts were based on nonfrontier approaches, which take no account of technical inefficiency but maintain that all changes to TFP are attributed to TC. Moreover, nonfrontier approaches can also be divided into two types: parametric methods, which mainly refer to average function methods, and nonparametric methods, such as methods based on exponential functions [3, 4] and on growth accounting [5, 6]. Scholars started exploring changes in TFP by frontier approaches, which were more rational, as the production frontier model was introduced in the mid-1990s. Unlike nonfrontier approaches, frontier ones prove more advantageous as they take technical inefficiency into account. Among them, there are parametric approaches, including deterministic frontier analysis (DFA) [7] and stochastic frontier analysis (SFA) [8], and there are nonparametric ones, mainly based on the Malmquist productivity index, which can be related to DEA [9–11] or SFA. Superior to other equivalents, the DEA approach can decompose TFP, requires neither priori assumptions of production function nor parametric estimates, and allows inefficiencies [12]. Given that, the particular approach has been widely adopted in related studies of TFP. Most scholars employing the DEA-Malmquist productivity index to study TFP in China's agriculture concluded that agricultural TFP was mainly driven by TC and that the decrease of EC was in sync with that of TC for most parts of China [13, 14]. The paper, therefore, attempts to employ the DEA-Malmquist index-based approach to decompose agricultural TFP of Hubei into TC and EC.

In the past decade or so, China's research on agricultural TFP has not only focused on different measurement approaches of TFP, but also placed greater emphasis on factors affecting agricultural TFP from various perspectives. The previous studies on how agricultural TFP contributes to economic growth, however, are few. Ji et al. demonstrated the positive impact of TFP on total agricultural output by measuring the change of TFP of 13 prefecture-level cities in Jiangsu province and by analyzing its contribution to agricultural output through a production function [15]. Zhang et al. measured the agricultural TFP of 9 cities in Guizhou, a southwestern province of China, from 2010 to 2017 and found that the impact of TC and EC on agricultural production of Guizhou was significant [16]. With the DEA-Malmquist index-based approach, Li et al. calculated agricultural TFP of China from 2004 to 2016 before concluding that agricultural TFP growth accounted for 53.7% of the China's agricultural output [17]. Building on these endeavors, this paper measures the agricultural TFP index of 12 prefecture-level cities in Hubei from 2009 to 2019 with the DEA-Malmquist nonparametric approach and decomposes it into TC and EC, which are then used to construct a C-D production function model. This way, it aims to explore how input factors, such as TC, EC, capital, and labor, contribute to agricultural output of Hubei and, on this basis, to put forward suggestions for reference in formulating agricultural policies in Hubei.

### 3. Data and Methods

**3.1. Malmquist Productivity Index in Agriculture.** Enlightened by research on consumption index by Swedish economist Malmquist [18], Caves et al. constructed Malmquist productivity index (Malmquist index, in short) [19], but without further study on how to measure the distance function. It was when Fare et al. had combined DEA with nonparametric linear programming that the index was widely applied [20].

As mentioned above, the Malmquist index takes into account technical inefficiency and decomposes TFP into TC and EC based on the CRS assumption. If returns to scale are variable, EC can be further divided into pure technical efficiency change (PE) and scale efficiency change (SE). Assuming that there are  $k$  decision-making units (DMU), where  $k = 1, 2, \dots, K$ , the input and output vectors of each period are  $x^{k,t} = (x_1^{k,t}, x_2^{k,t}, \dots, x_N^{k,t}) \in R_+^N$  and  $y^{k,t} = (y_1^{k,t}, y_2^{k,t}, \dots, y_M^{k,t}) \in R_+^M$  respectively, where  $t = 1, 2, \dots, T$ . Therefore, the input-oriented Malmquist index can be expressed as (1) under the CRS assumption.

$$\begin{aligned} M_i^k(x^{k,t+1}, y^{k,t+1}, x^{k,t}, y^{k,t}) &= \frac{D_i^{k,t+1}(x^{k,t+1}, y^{k,t+1})}{D_i^{k,t}(x^{k,t}, y^{k,t})} \times \left[ \frac{D_i^{k,t}(x^{k,t+1}, y^{k,t+1})}{D_i^{k,t+1}(x^{k,t+1}, y^{k,t+1})} \times \frac{D_i^{k,t}(x^{k,t}, y^{k,t})}{D_i^{k,t+1}(x^{k,t}, y^{k,t})} \right]^{1/2} \\ &= EC_i^k \times TC_i^k = PE_i^k \times SE_i^k \times TC_i^k. \end{aligned} \quad (1)$$

$D_i^{k,t+1}(x^{k,t+1}, y^{k,t+1})/D_i^{k,t}(x^{k,t}, y^{k,t})$  in (1) measures the EC of DMU  $k$  from period  $t$  to  $t + 1$ , indicating the impact of EC on TFP for a corresponding period, and EC can be further divided into PE and SE. The section in the square bracket measures TC of DMU  $k$  from period  $t$  to  $t + 1$ , which indicates the impact of advancement of production technology frontiers on TFP for a corresponding period.

We regard each prefecture-level city in Hubei as an independent DMU and create the optimal frontier of agricultural production in the province for periods under the same technical conditions. It is followed by a comparison of the relationship between the coordinates of agricultural production point of each DMU and the position of the optimal frontier. The technical efficiency of a DMU is at the highest level if the agricultural production point of the DMU is just on the frontier, and if the point is within the frontier, then the DMU is characterized by technical inefficiency. Meanwhile, with the time factor taken into consideration as mentioned earlier, we can compare the agricultural production point of a DMU with the mapping point of the optimal frontier and thus decompose agricultural TFP into TC and EC. Therefore, if  $TC = 1$  for a DMU, this means there is no technical change or innovation for the DMU from  $t$  to  $t + 1$ , whereas  $TC > 1$  (or  $TC < 1$ ) indicates technical progress (or setback). Similarly,  $EC > 1$  ( $EC < 1$ ) implies there is technical efficiency gain (loss) for the DMU from  $t$  to  $t + 1$ . Likewise,  $M = 1$  indicates that agricultural TFP in the DMU from  $t$  to  $t + 1$  stays unchanged;  $M > 1$  ( $M < 1$ ) denotes an increase (decline) of agricultural TFP.

3.2. *Production Function Modeling.* Given the above-mentioned measurement formula of the Malmquist index and with the initial year as a base period, the agricultural total factor productivity aggregate rate (TFPA) of a DMU can be calculated through the following equation:

$$TFPA_i^{k,T} = M_i^{k,t+1} \times M_i^{k,t+2} \times M_i^{k,t+3} \times \dots \times M_i^{k,T} = \prod_{j=1}^{T-t} M_i^{k,t+j}. \quad (2)$$

Likewise, the agricultural technological change aggregate rate (TCA) and agricultural technical efficiency change aggregate rate (ECA) of a DMU, with the initial year as a base period, can also be calculated by the following equation:

$$\begin{cases} TCA_i^{k,T} = \prod_{j=1}^{T-t} TC_i^{k,t+j}, \\ ECA_i^{k,T} = \prod_{j=1}^{T-t} EC_i^{k,t+j}. \end{cases} \quad (3)$$

$$\text{LnTV}_{it} = \lambda_0 + \lambda_1 \text{TFPA}_{it} + \lambda_2 \text{LnFERT}_{it} + \lambda_3 \text{LnLABOR}_{it} + \lambda_4 \text{LnMCHN}_{it} + \varepsilon_{it}, \quad (4)$$

$$\text{LnTV}_{it} = \delta_0 + \delta_1 \text{TCA}_{it} + \delta_2 \text{ECA}_{it} + \delta_3 \text{LnFERT}_{it} + \delta_4 \text{LnLABOR}_{it} + \delta_5 \text{LnMCHN}_{it} + \eta_{it}. \quad (5)$$

In models (4) and (5),  $i$  represents each prefecture-level city in Hubei;  $t$  denotes the year;  $\text{TV}_{it}$  indicates the total output (by 100 million yuan) of the agriculture, forestry, animal husbandry, and fishery of each prefecture-level city over the years;  $\text{TFPA}_{it}$ ,  $\text{TCA}_{it}$ , and  $\text{ECA}_{it}$  denote the aggregate rate of agricultural TFP, TC, and EC in each prefecture-level city over the years against the initial year, respectively;  $\text{FERT}_{it}$  denotes chemical fertilizer consumption (by 1000 tons) in each prefecture-level city over the years;  $\text{LABOR}_{it}$  indicates the number of workers (by 10,000 people) engaged in the agriculture, forestry, animal husbandry, and fishery of each prefecture-level city over the years;  $\text{MCHN}_{it}$  represents the total power consumption (by 10,000 kW) of agricultural machinery in each prefecture-level city over the years;  $\lambda_0$  and  $\delta_0$  refer to intercepts; and  $\varepsilon_{it}$  and  $\eta_{it}$  are random terms.

3.3. *Data Sources and Descriptive Statistics of Variables.* We collected 132-sample data about the agricultural input and output from 12 prefecture-level cities (excluding Enshi Tujia and Miao Autonomous Prefecture) in Hubei province from the year 2009 to 2019. All data are sourced from *Hubei Statistical Yearbook*, *Agricultural Yearbook of China*, and *National Agricultural Costs and Returns Compilation* from 2009 to 2019. The descriptive statistics of variables are shown in Table 1.

Considering the availability of data, we only take labor, land, chemical fertilizer, machinery power, and irrigation as input factors in our models and assume that other input such

Therefore, inspired by Kumar et al. [21] and Los et al. [22], we decompose the source of economic growth into three parts: TC, EC, and input factors such as capital and labor. We then put them into Cobb–Douglas production function and construct models (4) and (5) as follows. (Production function model (4) is formed by the undecomposed TFPA with input factors such as capital and labor; production function model (5) is comprised of the decomposed TCA and ECA, as well as input factors. Given that TFPA, TCA, and ECA are rates of change, logarithms of these three variables are not taken in the following models.)

as agricultural film, seeds, and seedlings exerts little influence on the output. In addition, the chemical fertilizer input is calculated according to the effective net amount applied. Labor input is represented by the year-end number of workers in agriculture, forestry, animal husbandry, and fishery, and machinery input by the total power of agricultural machinery. Land input is represented by the year-end sown area of crops, and irrigation input by effective irrigation area.

## 4. Empirical Results and Analysis

4.1. *Temporal Changes of Agricultural TFP and Its Decomposition in Hubei.* We employ the DEAP 2.1 software to compute Malmquist index and its decomposition for Hubei province as a whole from 2009 to 2019 and for each city of Hubei, respectively. The results, as shown in Table 2, illustrate that the Malmquist TFP index of Hubei’s agricultural sector grew by 5.6% on average, which was a remarkable increase from 2009 to 2019. In the same period, the annual average growth rate of total agricultural output in Hubei reached about 8.75%, suggesting that 64% of the agricultural output growth was attributed to increased productivity. The agricultural sector of Hubei, undoubtedly, saw considerable fluctuations in the TFP index. For example, the growth rates in 2010 and 2012 reached 20.8% and 15.4%, respectively, while there was a decline of 3.8% and 7.5% in 2017 and 2018, which to some extent reflected the unstable nature of agricultural production.

TABLE 1: Descriptive statistics for output and input variables.

Variable	Declaration	N	Mean	Standard deviation	Minimum	Maximum
TV	Total output value of agriculture, forestry, animal husbandry, and fishery (RMB 100 million) at 2019 prices	132	413.6	210.7	89.87	836.5
TFPA	TFP aggregate rate (%)	132	1.61	0.59	0.98	3.62
TCA	TC aggregate rate (%)	132	1.67	0.48	1	2.85
ECA	EC aggregate rate (%)	132	0.97	0.19	0.63	1.66
FERT	Chemical fertilizer consumption (1,000 tons)	132	236.7	148.1	43.58	606.1
LABOR	Number of workers in agriculture, forestry, animal husbandry, and fishery (10,000 people)	132	60.79	31.45	16.97	134.3
MCHN	Total power consumption of agricultural machinery (10,000 kW)	132	281.2	165.9	49.73	680.8
LAND	Year-end actual cultivated area (1000 hectares)	132	250.33	137.72	40.4	682.96
IRRI	Effective irrigation area (1000 hectares)	132	172.38	119.21	26	573.3

Note. TFPA, TCA, and ECA are calculated by (2) and (3). TV has been converted to current price based on price index of agricultural production. Source: State Economic Planning Commission and State Statistical Bureau (2009–2019).

TABLE 2: Temporal changes of the agricultural Malmquist index and its composition in Hubei (2009–2019).

Year	Malmquist index (TFP)	Technical change index (TC)	Technical efficiency change index (EC)	Pure technical efficiency change index (PE)	Scale efficiency change index (SE)
2009–2010	1.208	1.126	1.073	1.067	1.006
2010–2011	1.065	1.060	1.005	0.982	1.023
2011–2012	1.154	1.189	0.970	1.003	0.968
2012–2013	1.067	1.203	0.887	0.943	0.941
2013–2014	1.051	1.042	1.009	1.005	1.004
2014–2015	1.036	1.099	0.943	0.971	0.970
2015–2016	1.086	1.083	1.003	1.007	0.996
2016–2017	0.962	0.980	0.981	1.000	0.981
2017–2018	0.925	0.899	1.029	1.023	1.005
2018–2019	1.030	1.023	1.006	0.997	1.010
2010–2019	1.056	1.067	0.989	0.999	0.990

Note. TFP can be decomposed into TC and EC, whereas EC can be further decomposed into PE and SE. Source: computed by authors based on the data from Hubei Statistical Yearbook (2009–2019).

From the perspective of the composition of Malmquist index, it is agricultural TC that drives the growth of agricultural TFP in Hubei. From 2009 to 2019, the agricultural TC in Hubei increased by 6.7% annually, while the agricultural EC decreased by 1.1%. The TC value was greater than 1 throughout the sample period (excluding 2017 and 2018), suggesting that agricultural technology was advancing for most of the time. EC, however, was smaller than 1 in four years of the sample period, indicating a significant loss in technical efficiency. Technological progress, coupled with decreased efficiency, implied that the province came a long way in technological innovation in agriculture for the sample period, despite inefficiency in applying existing agricultural technology. The decomposition of EC showcased the fact that loss in agricultural EC resulted from the poor performance of PE and SE. During the sample period, PE and SE experienced a decline of 0.1% and 1% on average, respectively. This, therefore, explains that loss in agricultural EC for Hubei is mainly caused by decreased SE, a conclusion inconsistent with previous findings in other Chinese provinces [15]. The possible reason behind it is that agricultural production by small household farmers still prevails in Hubei, leading to the lag in promoting and applying cutting-edge technology. With that, greater efforts should be made to promote new agricultural technology and

encourage large-scale farming in a way to increase technical efficiency.

*4.2. Regional Difference in Agricultural TFP and Its Decomposition in Hubei.* According to the official geographical division, Hubei comprises three main regions, namely East Hubei, Central Hubei, and West Hubei. Boasting multiple lakes, the eastern part includes the cities of Wuhan, Huangshi, Ezhou, Xianning, and Huanggang. The central region consists of the cities of Jingmen, Jingzhou, Xiaogan, and Suizhou, and features a large expanse of plains, making it a granary for the province. The mountainous western part, also known as Northwest Hubei, comprises the cities of Shiyan, Yichang, and Xiangyang, as well as Enshi Autonomous Prefecture. (Hubei Province is comprised of 12 prefecture-level cities and Enshi Tujia and Miao Autonomous Prefecture. We only observed the realities of the 12 cities, excluding Enshi Autonomous Prefecture.)

In the view of regional distribution, 12 prefecture-level cities in Hubei saw an increase in agricultural TFP from 2009 to 2019, yet growth rates of the three regions varied remarkably. Central Hubei took the lead with a growth rate in agricultural TFP of 7.6%, followed by West Hubei (5.8%, slightly above the provincial average) and East Hubei (3.9%).

Among the 12 cities, the top three in terms of agricultural TFP growth rate were Jingmen (13.7%), Wuhan (9.2%), and Jingzhou (8.4%). 2 out of the 3 cities are located in Central Hubei. Among the bottom four cities in agricultural TFP, East Hubei accounted for 3 cities, namely Ezhou (3.7%), Huangshi (1.2%), and Huanggang (0.9%).

From the perspective of decomposition, agricultural TFP growth in East Hubei, Central Hubei, and West Hubei from 2009 to 2019 was driven by agricultural TC, which grew at an annual average rate of 6.1%, 8%, and 5.9%, respectively. The three regions saw different degrees of loss in EC. The situation in western Hubei was relatively optimistic, with an average annual efficiency loss of only 0.1%, while the eastern Hubei experienced the maximum efficiency change, with an average annual efficiency loss of 2.1%, which led to the situation that East Hubei ranked at the bottom in agricultural TFP growth despite a relatively developed economy. Moreover, half of the cities in Hubei witnessed technological progress and technical efficiency loss. Among them, half were in East Hubei, which suffered a low TFP growth rate as a result of decreased agricultural EC offsetting the contribution of TC to TFP growth. The increase of TFP in Wuhan, Ezhou, and Shiyan was totally boosted by TC, since EC of the 3 cities stayed unchanged during the study period. Among all the 12 cities, only three cities—Jingmen, Yichang, and Jingzhou—embraced an improvement both in TC and in EC. Through further decomposition of EC, it is not difficult to find that efficiency loss in Central Hubei and West Hubei was attributed to a loss in SE, not in PE, and that in East Hubei was due to a loss in SE and PE, with SE exerting a greater impact. This suggests that large-scale promotion of agricultural technology is expected to be made across Hubei province. Overall, the key to enhancing TFP across the board and to ensuring quality and sustainability in agriculture is the promotion of cutting-edge agricultural technology, the wide and standardized application of new technology, and an increase in agricultural technical efficiency (see Table 3).

**4.3. Contribution of Agricultural TFP and Its Decomposition to the Growth of Hubei's Agricultural Economy.** To measure the contribution of agricultural TFP and its decomposed factors (agricultural TC and EC) to the growth of the agricultural economy requires an estimate of unknown parameters in models (4) and (5). Prior to that, a coefficient test on variables is conducted to ensure that the models suffer severe multicollinearity (see Tables 4 and 5).

As shown in Tables 4 and 5, the correlation coefficients of independent variables are smaller than 0.8, except for LnMCHN and LnFERT. Thus, the variance inflation factor (VIF) is performed to ensure that the correlation between these two variables does not exert a serious impact on models (4) and (5). The results showed that the VIFs of all independent variables in model (4) are not greater than 7.65 and those in model (5) are not greater than 9. Therefore, the independent variables listed in Tables 4 and 5 can be included in models (4) and (5) at the same time.

According to the result of Hausman test, we chose to specify a two-way fixed-effects model to estimate the

TABLE 3: Regional differences of agricultural Malmquist index and its decomposition in Hubei.

Region	City	TFP	TC	EC	PE	SE
East Hubei	Wuhan	1.092	1.092	1.000	1.000	1.000
	Huangshi	1.012	1.058	0.957	1.000	0.957
	Ezhou	1.037	1.037	1.000	1.000	1.000
	Huanggang	1.009	1.051	0.959	0.997	0.962
	Xianning	1.044	1.068	0.978	0.978	1.000
	<b>Average</b>	<b>1.039</b>	<b>1.061</b>	<b>0.979</b>	<b>0.995</b>	<b>0.984</b>
Central Hubei	Jingmen	1.137	1.103	1.030	1.034	0.997
	Xiaogan	1.027	1.063	0.966	0.978	0.988
	Jingzhou	1.084	1.081	1.004	1.020	0.984
	Suizhou	1.057	1.073	0.984	0.987	0.997
	<b>Average</b>	<b>1.076</b>	<b>1.080</b>	<b>0.996</b>	<b>1.005</b>	<b>0.992</b>
West Hubei	Shiyan	1.041	1.041	1.000	1.000	1.000
	Yichang	1.055	1.044	1.010	1.000	1.010
	Xiangyang	1.079	1.093	0.987	1.000	0.987
	<b>Average</b>	<b>1.058</b>	<b>1.059</b>	<b>0.999</b>	<b>1.000</b>	<b>0.999</b>
Provincial Average		1.056	1.067	0.989	0.999	0.990

Note. The Malmquist index and its decomposition are the annual mean of each city from 2009 to 2019. Source: computed by authors based on the data from *Hubei Statistical Yearbook* (2009–2019). The bold values are the arithmetic means of TFP, TC, EC, PE, and SE for each region of Hubei.

TABLE 4: Correlation coefficient matrix of variables in model (4).

Variable	LnTV	TFPA	LnFERT	LnLABOR	LnMCHN
LnTV	1				
TFPA	0.361***	1			
LnFERT	0.764***	0.222**	1		
LnLABOR	0.779***	-0.104	0.788***	1	
LnMCHN	0.862***	0.440***	0.834***	0.760***	1

Note. Because of multicollinearity, the input of land and irrigation is excluded from the final model.

parameters, in which city-specific effects and time-specific effects were controlled by the product of time trend and city dummies. In order to ensure the reliability of the regression results, we also reported Pooled OLS estimators as a contrast. Table 6 displays the regression results of models (4) and (5), indicating the impact of the agricultural TFP aggregate rate (TC and EC) and other input factors on Hubei's agricultural output. The regression results below have passed the serial correlation test and the heteroscedasticity test.

The results presented in Table 6 suggest that the goodness of fit using Pooled OLS method was inferior to that controlling for two-way fixed effects. The latter's estimates, therefore, were used to discuss the results of models (4) and (5), respectively.

Model (4) indicates that agricultural TFP played a significant positive role in Hubei's agricultural output. To be specific, agricultural output grew by 0.302% on average with an increase of 1% in the TFP aggregate rate. That means increased agricultural TFP drove the growth of the province's agricultural economy. The estimates in model (5) show that both the decomposed factors of agricultural TFP, i.e., technological progress and efficiency enhancement, promoted the growth of Hubei's agricultural economy in an effective manner. Specifically, an increase of 1% in TCA and ECA led to a rise of 0.279% and 0.322%, respectively, in

TABLE 5: Correlation coefficient matrix of variables in model (5).

Variable	LnTV	ECA	TCA	LnFERT	LnLABOR	LnMCHN
LnTV	1					
ECA	0.027	1				
TCA	0.425***	-0.088	1			
LnFERT	0.764***	0.229***	0.117	1		
LnLABOR	0.779***	-0.041	-0.076	0.788***	1	
LnMCHN	0.862***	0.175**	0.415***	0.834***	0.760***	1

Note. Because of multicollinearity, the input of land and irrigation is excluded from the final model.

TABLE 6: Estimates on the impact of agricultural TFP and its decomposition on the growth of agricultural economy in Hubei.

Variable	Model (4)		Model (5)	
	Pooled OLS	Two-way fixed effects	Pooled OLS	Two-way fixed effects
TFPA	0.313*** (3.98)	0.302*** (3.48)		
TCA			0.554*** (6.93)	0.279*** (3.62)
ECA			0.198* (1.71)	0.322** (2.04)
LnFERT	-0.016 (-0.28)	0.094*** (7.73)	0.103* (1.90)	0.208*** (4.15)
LnLABOR	0.654*** (6.13)	0.055*** (6.51)	0.733*** (7.94)	0.405*** (3.49)
LnMCHN	0.234** (2.52)	0.014 (1.55)	0.023 (0.26)	0.290*** (2.64)
Constant	1.591*** (9.14)	0.890*** (6.37)	1.187*** (7.56)	0.588*** (3.24)
N	132.000	132.000	132.000	132.000
Adj-R <sup>2</sup>	0.808	0.969	0.854	0.968

Note. The figures in the parentheses are *t* statistics of estimates. \*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10%, respectively. The models include 11 dummy variables to control for two-way fixed effects, but the estimated coefficients are not included for brevity.

Hubei's average agricultural output. That means both technical innovation and technical efficiency change in agriculture can considerably enhance agricultural output of Hubei, with technical efficiency change contributing more to the growth of the province's agricultural economy. Given that, Hubei needs to attach greater importance to the R&D of agricultural innovations and the promotion of existing cutting-edge technology.

From the perspective of input factors, estimated results of models (4) and (5) suggest that chemical fertilizer, labor, and machinery input all boosted the growth of Hubei's agricultural economy. Nonetheless, these input factors made a far less contribution to agricultural output than TFP did. This indicates that although the conventional input factors of production drove the growth of the agricultural economy, its contribution was limited. The high-quality and sustainable development of Hubei's agricultural sector hinged more on the innovation of agricultural technology and the improvement of agricultural technical efficiency.

*4.4. Contribution of Agricultural TFP and Its Decomposition to Agricultural Economic Growth in East Hubei, Central Hubei, and West Hubei.* Table 7 shows how the agricultural TFP aggregate rate (TC and EC) and other input factors in East Hubei, Central Hubei, and West Hubei make an impact

on their respective agricultural output. Similarly, we controlled for two-way fixed effects using the product of city dummies and time trend term for each region. As shown in model (4), agricultural TFP in the three regions contributed significantly to their growth of the agricultural economy, with Central Hubei taking the lead and West Hubei ranking at the bottom. To be specific, a rise of 1% in the TFP aggregate rate for Central Hubei and West Hubei brought about an increase of 0.72% and 0.166% in average agricultural output, respectively. The impact of the TFP aggregate rate on agricultural output for West Hubei was even less than that of fertilizer input and machinery input on its agricultural output.

As presented in model (5), TCA and ECA made a greater contribution to agricultural output in Central Hubei than in East Hubei and West Hubei, whereas the impact of TCA on the growth of the agricultural economy was the smallest in West Hubei compared to the other two regions. The estimates on Central Hubei and West Hubei showed that the contribution of ECA to agricultural output was greater than that of TCA, consistent with the above-mentioned regression results about the entire province. As far as regression results about East Hubei were concerned, the impact of TFP growth on agricultural output (0.249%) was overwhelmingly attributed to TCA (0.248%), and ECA contributed little to agricultural output probably due to loss in technical efficiency, which, as mentioned above, was more severe in East

TABLE 7: Estimates about the impact of agricultural TFP and its decomposition on agricultural economic growth in East Hubei, Central Hubei, and West Hubei.

Variable	Model (4)			Model (5)		
	Eastern Hubei	Central Hubei	Western Hubei	Eastern Hubei	Central Hubei	Western Hubei
TFPA	0.249*** (5.59)	0.720*** (10.89)	0.166** (2.59)			
TCA				0.248*** (5.71)	0.710*** (10.39)	0.181*** (3.02)
ECA				0.173 (1.16)	1.007*** (10.95)	0.828*** (3.57)
LnFERT	0.222*** (7.75)	-0.293 (-1.23)	0.664*** (6.35)	0.212*** (7.11)	-0.178 (-0.80)	0.650*** (6.46)
LnLABOR	0.066 (1.32)	0.933*** (12.20)	-0.249 (-1.10)	0.088* (1.68)	0.930*** (12.76)	-0.147 (-0.67)
LnMCHN	0.723*** (17.39)	0.045 (0.27)	0.290** (2.76)	0.712*** (16.84)	-0.127 (-0.80)	0.266** (2.72)
Constant	0.157 (1.29)	2.210*** (5.96)	1.137* (1.82)	0.022 (0.10)	1.531*** (4.62)	0.057 (0.07)
N	55.000	44.000	33.000	55.000	44.000	33.000
Adj-R <sup>2</sup>	0.995	0.980	0.990	0.995	0.982	0.991

Note. The figures in the parentheses are *t* statistics of estimates. \*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10%, respectively. The models include dummy variables to control for two-way fixed effects, but the estimated coefficients are not included for brevity.

Hubei than in the other two regions. In short, model (5) suggests that the influence of ECA on agricultural economic growth was more profound than that of TCA.

## 5. Conclusions and Implications

Building on statistics from 12 prefecture-level cities in Hubei and employing the DEA-Malmquist productivity index, this paper measures and decomposes agricultural TFP of Hubei. On this basis, the C-D production function is adopted to empirically study the contribution of TFP and its decomposed elements to the agricultural economic growth in Hubei. We can draw the following conclusion based on the analysis above.

First, agricultural TFP of Hubei showed volatile growth, with technical progress and technical efficiency loss coexisting. The TFP index grew by 5.6% on average from 2009 to 2019, and 64% of the increase in agricultural output came from the growth in agricultural TFP, which was driven more by technological progress than by higher technical efficiency. That means Hubei produced fruitful results in innovation in agricultural technology over the decade, yet lacking the application and promotion of existing technologies.

Second, loss in agricultural technical efficiency was mainly attributed to a decline in SE, in addition to decreased PE. Therefore, more efforts need to be made to apply and promote frontier technology, encourage large-scale agricultural production, and develop new technical standards. This will allow for a wide application of new technology and further increase technical efficiency, particularly scale efficiency, for Hubei's agricultural sector.

Third, the TFP growth among cities and regions differed remarkably. From 2009 to 2019, agricultural TFP in East Hubei, Central Hubei, and West Hubei was on the rise but to varying degrees, with Central Hubei, the province's granary, seeing the largest growth, followed by West Hubei and East Hubei. Such a difference depends on the different agricultural resource endowments and the different agricultural output of each region.

Fourth, agricultural TFP growth in East Hubei, Central Hubei, and West Hubei was driven by TC. During the sample period, technical efficiency declined disproportionately across

the three regions, with East Hubei seeing the largest drop. An analysis of decomposed factors showed that loss in technical efficiency in Central Hubei and West Hubei resulted from a decrease in SE rather than in PE and that technical efficiency loss in East Hubei was caused by both SE and PE, with the former exerting a greater impact. Thus, to enhance TFP across the province and ensure quality and sustainability in agriculture, the key is to embrace the large-scale and standardized application of technology and increase agricultural technical efficiency.

Fifth, the growth of Hubei's agricultural economy depended on the increase of agricultural TFP (TC and EC). Moreover, an increase of 1% in the TFP aggregate rate led to an uptick of 0.302% in average agricultural output, which was significantly elevated by technological innovation and efficiency. The impact of EC on the growth of the agricultural economy was larger than that of TC. Compared to input factors such as chemical fertilizer, labor, and machinery, TFP growth had a far greater impact on the growth of the agricultural economy. Given that, Hubei should focus more on developing agricultural innovations and promoting existing cutting-edge technology.

Sixth, agricultural TFP growth (especially TC) made a significant, positive contribution to the growth of the agricultural economy in the three regions of Hubei, with Central Hubei being the largest contributor, followed by East Hubei and then by West Hubei. Even on the decomposition of TFP, the contribution of TC and EC in Central Hubei to agricultural output was larger than that in the other two regions. In terms of TC's contribution to agricultural output, West Hubei played a smaller role. In East Hubei, the impact of agricultural TFP growth on agricultural economic growth was overwhelmingly attributed to TC.

Given the aforementioned conclusions, we offer some suggestions as follows. Firstly, the focus should be on how agricultural TFP significantly contributes to the growth of the local agricultural economy, before driving TFP growth as a way to develop a quality and sustainable agricultural economy in Hubei. Secondly, priority should be given to the increase of technical efficiency, particularly scale efficiency, which profoundly affects the growth of the agricultural economy. Governments should focus more on developing

new technologies, promoting them on a large scale, setting up new technical standards, and offering relevant training to agricultural technology promoters. Thirdly, Hubei should fully grasp the difference in the regional growth of the agricultural economy before developing tailored and targeted measures and policies on the basis of the distinct realities of each region. Specifically, Central Hubei should maintain its strengths and make up for the shortcomings of low scale efficiency; West Hubei should bolster investment in the R&D of new technology and support for growing industrial chains; East Hubei should step up efforts to promote the large-scale application of agricultural technology. Last but not least, the rational input of production factors should be ensured. To this end, increased efforts should be made to develop and apply agricultural machinery and equipment in East Hubei; the regime of agricultural labor market allocation in Central Hubei should be optimized; the consumption of chemical fertilizer in West Hubei should be effectively controlled, on top of a wide application of agricultural machinery and equipment. In a word, tailored and targeted measures should be adopted to maximize the growth of the agricultural economy throughout Hubei.

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

### Acknowledgments

This research was supported by Major Program of National Social Science Foundation of China (Grant no. 20AGL006), Humanities and Social Sciences Project of Ministry of Education of China (Grant no. 19YJC630233), and Educational Commission of Hubei Province of China (Grant no. 19Q129).

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