An empirical study on the impact of human capital on cost efficiency: taking the main corn production areas in China as an example

Wang Qian and Lv Jie

ABSTRACT

Improving cost efficiency is one of the main ways to reduce the production cost of agricultural products and increase farmers’ income. Human capital is an important way to improve cost efficiency. This article takes five major corn production areas as an example, uses data envelopment analysis to measure the cost efficiency and makes an empirical analysis of the impact of human capital on cost efficiency and its action path by using bidirectional fixed-effect model. It is found that the impact of educational human capital on cost efficiency presents a positive ‘U’ shape, and there are differences among different regions through technical efficiency and allocation efficiency paths. Healthy human capital has a significant positive impact on cost efficiency, but with the increase of the number, its role will gradually weaken, except for the southwest region, and its impact path is allocation efficiency. The impact of technical human capital on cost efficiency shows a positive ‘U’ type change, and the change of each production area is roughly the same as the whole. Its impact on cost efficiency is mainly realised through allocation efficiency. This article provides a theoretical basis for different policy measures to better play the role of human capital in improving cost efficiency in China.

Introduction

Improving cost efficiency is one of the main ways to reduce the production cost of agricultural products and increase farmers’ income. The level of farmers’ income is related to farmers’ enthusiasm and national food security. In 2017, the No. 1 Central Document explicitly pointed out that the structural reform of agricultural supply side should be based on ensuring the national grain security, and the main goal is to increase farmers’ income and ensure effective supply. The No. 1 Central Document once again raised the issue of peasant income and narrowing the income gap between urban and rural residents as a ’14th Five-Year’ period in 2019 and 2021 (Xiaochen 2020). As we all know, the most fundamental income of farmers comes from land. In case of stable grain prices, improving cost efficiency and reducing production costs are effective ways and realistic choices to improve farmers’ income.

Human capital plays a positive role in agricultural development. Human capital is not only the ‘whole participant’ in the production process of food crops but also the ‘decision maker’ of factor matching. The quality of farmers has a positive role in improving the level of agricultural technology. To change the production mode of traditional agriculture, we need to continuously increase the supply of agricultural intellectual resources (Shengli and Shijiang 2016). In 2021, the No. 1 Central Document put forward the instructions of ‘Improving the quality of rural education’, ‘Developing occupation skills education and training’ and ‘promoting healthy rural construction’, which showed the importance of the government’s importance to rural human capital.

The existing literature has verified the positive role of human capital in agriculture. A study by Yan-Hua and Li (2006) proved that there was a positive relationship between labour force education and agricultural technical efficiency from different perspectives. A study by Wei et al. (2018) and Xiao et al. (2018) pointed out that the impact of human capital on agricultural production efficiency would change with the scale of cultivated land. However, there are also some literatures that the contribution of human capital in agricultural production is not significant. Jianhua (2011) and Jingbo and Yuan (2020) found that the human capital had a positive role in promoting rural economic growth, but the
contribution rate was low. Even a few scholars have shown that the effect of human capital on rural economic growth was not significant and even sometimes played a negative role (Sanusi and Singh 2016; Xuejiao and Haifeng 2016). Most of the existing literatures focus on the relationship between human capital and agricultural production efficiency or agricultural economic growth. Few literatures focus on the relationship between human capital and cost efficiency, some just put human capital into production as a factor of labour production, and calculate its cost efficiency value together with other factors, or the educational human capital as a proxy variable of human capital mixed with other factors, simply analyse its influence value, ignoring the status and role of healthy human capital and technical human capital (Yuqiu and Lei 2016; Qiuxia et al. 2018). The analysis of the role of human capital is not comprehensive and in-depth. What is the impact of human capital on corn cost efficiency? What are the paths of action? Is there any difference in the situation of each production area? To clarify the aforementioned problems is conducive to the cultivation of human skills of farmers in major corn production areas, so that human capital can give full play to its positive role in corn planting, improve cost efficiency, reduce planting costs and improve income (Saravanan et al. 2015; Gao et al. 2020). A merchandise possibilities frontiers concept with output port generated using the same inputs was used. Soybeans and food grain fluctuations were calculated using the framework (Mariyono 2019).

Theoretical analysis and hypothesis

The concept of human capital and related theories

Schultz, an American economist, defined human capital as knowledge, ability and health embodied in human body. The author thinks that there is a positive correlation between human capital stock and per capita output rate, which is the source of social progress. Becker interpreted the meaning of human capital from a microperspective and believed that besides knowledge and skills, health and life span are also important components of human capital (Xiaochen 2020). Chinese scholar pointed out that human capital refers to the capital that people spent on human health care, education, training and other aspects. The human capital was mainly measured by the health status, education level and skill level of the labour force (Miller and Upadhyay 2000; Shengli and Shijiang 2016). Although different scholars have different interpretations of the concept of human capital, they have reached a consensus on its connotation, that is, knowledge, skills, good quality and all the abilities that can improve labour productivity condensed in natural people through education, training and other formal and informal learning processes, as well as through health investment, labour migration and other means (Yan-Hua and Li 2006). Based on the aforementioned theories, this article divides human capital into three parts: educational human capital, healthy human capital and technical human capital.

Cost efficiency measurement and decomposition

Cost efficiency refers to the rationality of resource allocation and the cost of the same output level under a certain level of technology and price (Wei et al. 2018). Its essence is the ratio of unit frontier cost to actual cost, which reflects the gap between actual cost and optimal frontier cost. Cost efficiency is a comprehensive index to measure the technical efficiency and allocation efficiency, which reflects the technical and economic efficiency in the optimal state of technology and element allocation (Wei et al. 2020).

In the case of constant returns to scale,

Cost efficiency = Technical efficiency × Allocation efficiency.

In the case of variable returns to scale,

Cost efficiency = Pure technical efficiency × Scale efficiency × Allocation efficiency.

Because agricultural production is in line with the characteristics of constant returns to scale (Jingbo and Yuan 2020), this article sets the condition of constant returns to scale to calculate corn cost efficiency.

Analysis on the mechanism of human capital’s influence on cost efficiency

The influence of educational human capital on cost efficiency

The higher the education level of farmers is, the faster they learn advanced agricultural technology and management experience, which provides the knowledge base for farmers to learn new skills (Xiao-Yong and Qiu-Ping 2012). The improvement of knowledge reserve shortens the time for the application of advanced technology to actual production and is conducive to the improvement of technical efficiency (Schultz 1961). However, when the comparative efficiency of agricultural production is lower than that of other
industries, farmers with higher education level tend to non-agricultural production, which is not conducive to the improvement of technical efficiency. Therefore, the impact of educational human capital on technical efficiency is uncertain (Mankiw et al. 1992).

The planting willingness of the higher education level of farmers is not strong, under the guidance of advanced production technology, and they are more inclined to use mechanical equipment or fertiliser and other biotechnology to replace labour, changing the original ratio of production factors, so that the allocation efficiency tends to be optimal (Farrell 1957). However, due to the influence of the law of diminishing marginal returns of factors, once the ratio of factors exceeds the optimal ratio, the allocation efficiency will decline. Therefore, the impact of educational human capital on allocation efficiency is uncertain (Banker et al. 1984). For calculating frontiers business operations, panellists publicly available data on input–output crop yields in 23 districts from 1993 to 2013 are used (Mariyono 2014).

Hypothesis 1: Educational human capital acts on cost efficiency through two paths of technical efficiency and allocation efficiency, but its impact on technical efficiency and allocation efficiency is uncertain, so its impact on cost efficiency is uncertain (Phillips and Marble 1986).

The influence of healthy human capital on cost efficiency
Corn planting production is similar to a kind of repetitive physical labour, which requires high physical strength of farmers. Given appropriate growth circumstances, one corn plant will yield among two and four ears of corn. Early variants yield fewer eggs, whereas later-maturing cultivars produce somewhat more. How much corn you obtain will be mainly determined through how well you care for the crop. Corn is a heavy feeder that requires rich and healthy soil. Healthy human capital can provide long effective labour time and abundant labour supply, which directly promotes technical efficiency (Schultz 1961). At the same time, healthy body provides basic guarantee for farmers’ skill learning, which indirectly promotes the improvement of agricultural technical efficiency. Therefore, healthy human capital has a positive effect on corn technical efficiency (Battese and Coelli 1995).

Compared with non-healthy workers, healthy workers have advantages in ‘rational’ choice. On the one hand, as an input factor, healthy human capital participates in labour and forms a reasonable total allocation with other production factors (Ahmed and Melesse 2017). On the other hand, due to the strong adaptability of labour intensity, it can avoid the unconditional excessive dependence on biotechnology investment such as machinery or fertiliser due to physical reasons, resulting in the waste of factor allocation, so as to make a more ‘rational’ choice. Healthy human capital is conducive to the improvement of allocation efficiency (Mukherjee et al. 2017).

Hypothesis 2: Healthy human capital improves cost efficiency by positively promoting technical efficiency and allocation efficiency (Oumer et al. 2020).

The influence of technical human capital on cost efficiency
Workers participate in skill training can learn the latest agricultural technology and access to the latest agricultural information and pest control measures, which is conducive to the improvement of technical efficiency.

The improvement of workers’ skills can improve the management level of their own cultivated land, enhance the utilisation and management of existing resources and capital, so as to improve the allocation efficiency. But for the sake of income, skilled labour is often engaged in non-agricultural production, skills cannot be applied to their own corn planting. The positive impact on allocation efficiency is not significant. Therefore, the impact of technical human capital on allocation efficiency is uncertain. Human capital influences productivity expansion as well as may aid in the development of an economic system by broadening its people’s knowledge besides abilities (Luther et al. 2018). The quantity of skilled labour required is determined through the degree of productivity expansion caused by consumption expenditure besides business profits.

Hypothesis 3: Technical human capital has a positive effect on the improvement of corn technical efficiency, and its impact on allocation efficiency is uncertain. Therefore, the impact of technical human capital on corn cost efficiency is uncertain (Ojo et al. 2020). Human capital is based on three categories named as education, healthy and technical. All these are combined to form a human capital and the data’s based on the specified categories are transferred into technical efficiency and allocative efficiency which is the fundamental element for computing cost efficiency (Figure 1).

Model setting and variable selection
Cost efficiency model and variable selection
Model setting
The analysis of cost efficiency includes nonparametric method and parametric method. The former is generally estimated by data envelopment analysis (DEA), while the
latter is generally measured by stochastic frontier production function. The nonparametric method does not need to set specific function form. Compared with the parameter method, this method is not limited by the assumptions of production function, and can avoid the measurement error caused by improper setting of index dimension and assumptions (Jingbo and Yuan 2020). A nonparametric approach for calculating the relative efficiency of reducing carbon emissions within a collection of identical decision-making units (DMUs) with numerous inputs as well as outputs is termed as DEA. DMUs in this context might be hospitals, bank offices, schools, stores, businesses, and so on. It is used to quantify the production efficiency of DMUs empirically. The nonparametric technique is a form of statistic that makes no preconceptions about the patterns’ features (its variables) else even if the observational values are largely qualitative. The predictive performance of nonparametric techniques is established through information instead of being set a priori. The word nonparametric does not indicate that all models are totally devoid of characteristics, but because the quantity in addition to the type of the criteria are variable besides not predetermined. A nonparametric approximation of a posterior distribution is a histogram. The DEA method can decompose the cost efficiency into the form of technical efficiency and allocation efficiency that is Nieto et al. (2019):

\[ CE = \frac{C^*(p, Q_0)}{C(p, Q_0)} \]  

The value of CE is between [0,1]. The closer it is to 1, the more efficient it is. The closer to 0, the more the inefficient is.

The common reference string (CRS) paradigm in cryptography encapsulates the presumption that a trustworthy arrangement occurs in which all relevant stakeholders have exposure towards the same string CRS obtained from certain dispersion D. Systems that have been proved secure under the CRS model are reliable if the configuration was done properly. CRS compels financial companies to recognise their client’s tax residence in addition to provide opportunities in foreign tax residents’ bank deposits to provincial tax department. It also necessitates the communication of data betwixt tax department in participating nations. In the CRS model, cost efficiency is divided into technical efficiency and allocation efficiency that is Nieto et al. (2019):

\[ CE = TE \times ATE \]  

Variable selection and descriptive statistics
When selecting the input factors of corn production cost efficiency, the research methods of Jianhua (2011) and
Table 1. Input and output index of cost efficiency and selection basis.

| Project variable | Variable description |
|------------------|----------------------|
| Output indicators| Output value of main products (y) |
|                  | Corn seed consumption per mu (kg/mu) |
|                  | Amount of chemical fertiliser used after conversion to pure corn per mu (kg/mu) |
|                  | Leasing operation power (mach) |
|                  | Labour input (labour) |
|                  | Seed price (sp) |
|                  | Fertiliser price (fp) |
|                  | Rental operation price (mp) |
|                  | Labour price (lp) |

Table 2. Statistical description of input and output variables.

| Variable | Obs  | Mean     | Std. Dev. | Min     | Max     |
|----------|------|----------|-----------|---------|---------|
| y        | 435  | 578.62   | 317.062   | 106.58  | 1494.23 |
| breed    | 435  | 2.812    | 0.755     | 0.694   | 8.66    |
| fer      | 435  | 22.273   | 8.953     | 6.4     | 78.15   |
| mach     | 435  | 11.230   | 6.668     | 2.39    | 61.369  |
| labour   | 435  | 0.098    | 0.147     | 0.0009  | 1.494   |
| sp       | 439  | 12.123   | 9.664     | 0.928   | 36.436  |
| fp       | 439  | 3.881    | 1.562     | 0.412   | 7.196   |
| mp       | 439  | 28.625   | 28.486    | 2.9     | 89.827  |
| lp       | 439  | 622.096  | 609.574   | 0.034   | 2825.677|

Xuejiao and Haifeng (2016) are referred, and the variables are from the provincial data. The output value of corn per mu is taken as output variable. The labour force and material per mu of corn are selected as input variables. Among them, the material input includes the quantity of seeds, the quantity of fertiliser, the power of leasing operation, labour input and the price of four factors. Specific variable description in Table 1.

The data come from the Compilation of National Agricultural Product Cost Benefit Data, China Agricultural Yearbook, China Rural Statistical Yearbook and China Agricultural statistical data from 1990 to 2019 (Table 2).

The model of the influence of human capital on cost efficiency

Model setting

To explore the impact of human capital on cost efficiency, human capital is divided into three dimensions: educational human capital, healthy human capital and technical human capital. Each dimension is taken as the core explanatory variable, and cost efficiency as the explained variable. In this article, there are 15 cross-sectional data, and the length of time is 30 years, which belong to the long panel data. Long panel data is a special bidirectional fixed-effect model. The bidirectional fixed-effects regression technique has always been the industry standard for predicting impact of the intervention from dynamic panel. Several application researchers have used the 2FE estimation to account for both unknown unit-specific as well as time-specific factors. In statistics, a regression equation is used to determine whether else not there is a link between two groups of information. If you examine a child's height annually, you could discover how they grow around three feet yearly. A regression equation may be utilised to predict the trend (increasing three inches every year). Three regression equations are established as follows:

\[ ce_i = \alpha_0 + \alpha_1 edu_i + \sum \alpha_i X_i + u_i + \gamma_i + \epsilon_i \] (3)

\[ ce_i = \beta_0 + \beta_1 health_i + \sum \beta_i X_i + u_i + \gamma_i + \epsilon_i \] (4)

\[ ce_i = \delta_0 + \delta_1 tech_i + \sum \delta_i X_i + u_i + \gamma_i + \epsilon_i \] (5)

where i is the province, t is the year and \( ce_i \) stands for cost efficiency. The first term of the three equations is a constant term. \( edu_i \) is education human capital, \( health_i \) is health human capital and \( tech_i \) is technical human capital. \( X_i \) is the control variable, \( u_i \) is used to control regional fixed effect, \( \gamma_i \) is used to control the time fixed effect and \( \epsilon_i \) represents the error term. According to \( \alpha_1 \) in model (3), it can judge the influence degree of education human capital on cost.
efficiency; according to $\beta_1$ in model (4), it can judge the influence of health human capital on cost efficiency; according to $\delta_1$ in model (5), it can judge the influence of skilled human capital on cost efficiency.

**Variable selection and descriptive statistics**

In the selection of human capital indicators, the average years of education or the proportion of different education levels are usually used to measure educational human capital in the world (Deepa et al. 2020; Orjuela et al. 2020). Healthy human capital refers to the cost of personal health expenditure, including medical services, health nutrition and health care expenses paid by individuals. In this article, the ratio of healthcare expenditure to living consumption is used to represent the health situation. Because of variations in the development of health expenditure relative to overall economic growth, the proportion of expenditure on health care products, as well as services contrasted to consumption expenditure might fluctuate significantly. Following a period of instability all through the financial downturn, the average proportion has been reasonably constant in latest days, as development in OECD healthcare expenditures has closely tracked growth in the economy. Technical human capital is represented by the proportion of technical training graduates in rural population. The control variables are the proportion of female labour force in the total labour force in each province. The net income of families in each province or the disposable income of each person in each province. In logarithmic form.

**Measurement of human capital and cost efficiency**

**Measurement of human capital**

This paper uses three dimensions of educational human capital, healthy human capital and technical human capital to represent the level of human capital. Specific data are shown in Table 4. The average education level of farmers engaged in planting in the main corn production areas in China is mostly concentrated in junior high school level, with an average of 7.59 years. Health care accounts for 7.22% of total household expenditure, which means that the health level of Chinese farmers is better. In China, the average proportion of technical training graduates in rural population is only 0.115%, which indicates that the level of technical human capital is low. In order to analyse the development of human capital in China’s main corn production areas, this paper further divides the human capital into production areas, as shown in Table 5.

Due to the limited space, this paper only reports the average value of human capital in each production area. The results show that the education level of farmers in Northeast and North China is relatively high, with an
average of 7.955 years. The health level of farmers in Northeast China is higher than that in Northwest and Southwest China.

**Measurement of cost efficiency**

In this article, DEAP2.1 software is used to estimate model (1) CRS model. The estimated results are shown in the table below. The average cost efficiency of main corn production areas in China is 0.705, which is in the middle level. The cost efficiency gap between provinces is large. The highest value is 1, which is in the optimal cost efficiency level, and the lowest value is 0.325, which is quite different from the optimal value. Technical efficiency and allocation efficiency can be obtained by decomposing cost efficiency, as shown in Table 6.

From the perspective of regional differences, the cost efficiency of corn in northeast region is the highest, while that in southwest region is the lowest. The technical efficiency of each production area is obviously better than its allocation efficiency, especially in the Southwest and Northwest areas (Table 7).

**The stationary test of the relationship between human capital and cost efficiency**

**Unit root test**

To determine the appropriate measurement method, the unit root test is carried out on the model. In this article, limited liability corporation (LLC) test, IPS test, Fisher D-fuller test and Fisher Pearson test are selected to test the unit root of each variable.

In the United States, a LLC is a corporate structure that shields its owners from personal accountability for the firm’s debts else liabilities. It is a composite enterprise that incorporates the features of a company as well as that of a traditional partnership. The null hypothesis of the IPS unit root test states that entire considered series have an order of integration else, to put it another way, are quasi. As a result of this, the rejecting of null implies that certain sequences are stable else approaching to respective norms throughout time. In time series information, a unit root test determines whether else not a data is stationary then comprises of a normality test. The existence of a unit root in a response variable establishes the hypothesis, whereas the appearance of a given time series characterises the second hypothesis. Fisher’s test, which is dependent on the $p$-values of independent unit root tests, implies that all sequence is quasi under the normality test, as opposed towards the potential substitute that at least one period in the array is stable.

Original hypothesis $H_0$: all variables have unit roots. The results show that in the above four test methods, the explained variable $ce$ rejects the original hypothesis and is a stationary series. The core explanatory variables $Edu$, tech and health, as well as the control variables in the four test methods, at least three test methods reject the original hypothesis and are stationary series.

**Autocorrelation, heteroscedasticity and cross-sectional correlation tests**

The intra-group autocorrelation, inter-group heteroscedasticity and inter-group contemporaneous correlation tests are performed on model (3). The results show that there is no intra-group autocorrelation in the model, but there are inter-group heteroscedasticity and inter-group contemporaneous correlation (see Table 8). To solve the aforementioned problems, this article uses the generalised least square method for estimation, the advantage of which is that it can solve the above two problems at the same time and is the most efficient. Owing to the limited space, only the test results of model (3) are reported. When there is a specific level of similarity among the predicted values in a regression model, generalised least squares is a method for estimating the independent variables in a regression model. The least squares technique is a systematic test for determining the best suitability for a group of data through minimising the total of deviations or contamination from the displayed curve. To forecast the behaviour of predictor variable, least squares regression is used. The

---

**Table 5. Human capital of each production area (mean value).**

| Variable | Northeast China | North China | East China | Southwest China | Northwest China |
|----------|----------------|-------------|------------|-----------------|----------------|
| edu      | 7.953          | 7.964       | 7.724      | 6.87            | 7.138          |
| health   | 8.407          | 7.210       | 6.445      | 6.084           | 7.846          |
| tech     | 0.072          | 0.070       | 0.062      | 0.098           | 0.284          |

**Table 6. Cost efficiency value and decomposition of corn in each production area (mean value).**

| Variable | Obs | Mean  | Std. Dev. | Min | Max |
|----------|-----|-------|-----------|-----|-----|
| ce       | 435 | 0.705 | 0.173     | 0.325| 1   |
| te       | 435 | 0.912 | 0.112     | 0.405| 1   |
| ate      | 435 | 0.769 | 0.143     | 0.352| 1   |

**Table 7. Cost efficiency value and decomposition of corn in each production area (mean value).**

| Variable | Northeast China | North China | East China | Southwest China | Northwest China |
|----------|----------------|-------------|------------|-----------------|----------------|
| ce       | 0.822          | 0.788       | 0.737      | 0.487           | 0.605          |
| te       | 0.929          | 0.959       | 0.918      | 0.850           | 0.879          |
| ate      | 0.880          | 0.821       | 0.780      | 0.58            | 0.688          |
An empirical study on the impact of human capital on cost efficiency

Cost estimation is just a strategy for determining cost estimations. It is the ash outlay for helping to strengthen, as well as evaluate programs in software engineering. Its factors are important techniques else quantitative solutions included to predict the product cost else operation.

The influence of human capital on cost efficiency

To test the impact of human capital on cost efficiency, according to the empirical model selected previously, the calculated cost efficiency is taken as the dependent variable, and the educational human capital, healthy human capital and technical human capital are taken as the core explanatory variables respectively, and the proportion of women in planting, per capita disposable income, the corn disaster area and the proportion of agricultural expenditure are controlled and estimated by regression.

To avoid the multicollinearity problem among the three core explanatory variables and ensure the stability of the regression results, this article makes a regression analysis on each core explanatory variable and establishes three models. Model (1) focuses on the impact of educational human capital on cost efficiency. Model (2) focuses on the impact of healthy human capital on cost efficiency. Model (3) focuses on the impact of technical human capital on cost efficiency. To verify the robustness of the impact of each human capital dimension on cost efficiency changes, this article adds the square of three core variables as explanatory variables in each model. At the same time, considering the synergy among the three core explanatory variables, the cross terms of educational human capital and healthy human capital and technical human capital are added to the model (1). In model (2), the cross term of healthy human capital and technical human capital is added, to verify whether the three core variables have synergistic effect in the change of cost efficiency. Table 9 reports the model estimates.

According to the results in the table, in the model (1), the influence coefficients of educational human capital on cost efficiency are significantly negative at the 1% level, but the square term turns positive. It shows that the impact of educational human capital on cost efficiency is positive 'U' type. It shows that if the educational human capital increases gradually and exceeds a certain limit, it can improve the cost efficiency. The cross coefficient of educational human capital and healthy human capital is significantly negative, which indicates that educational human capital plays a negative role in cost efficiency by acting on healthy human capital. The cross coefficient of educational human capital and technical human capital is 0.014 at the 1% significant level, which indicates that educational human capital indirectly promotes the improvement of cost efficiency by influencing technical human capital. In model (2), the impact of healthy human capital on cost efficiency is significantly positive, but its square term is significantly negative, which indicates that the impact of healthy human capital on cost efficiency is inverted 'U'. It shows that healthy labour force can promote the improvement of cost efficiency to a certain extent, but there is a moderate quantity. If the effective labour supply exceeds or is less than the appropriate amount, it will have a negative effect on cost efficiency. The cross-regression coefficient of healthy human capital and technical human capital is 0.01, which indicates that healthy human capital plays a positive role in promoting cost efficiency through technical human capital. In model (3), the effect of technical human capital on cost efficiency does not pass the significance test. However, the square terms all passed the 1% significance test, and the influence coefficient was 0.165. It shows that the increase of technical human capital has a positive effect on cost efficiency.

In terms of control variables, the effects of per capita disposable income and corn disaster area on cost efficiency are significantly negative in all models. The proportion of women is significantly positive in model (2) and model (3), indicating that the higher the
Table 9. Impact of human capital on cost efficiency and path analysis.

| Variable      | Cost efficiency |           |           |           |           | Allocation efficiency |
|---------------|-----------------|-----------|-----------|-----------|-----------|-----------------------|
|               | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 |
| edu           | −0.212*** | (0.002) |           | 0.198*** | (0.001) |           | −0.346*** | (0.000) |
| edu*health    | −0.001*** | (0.002) |           | 0.0001   | (0.654) |           | −0.0005 **| (0.000) |
| edu*tech      | 0.014***  | (0.000) |           | 0.004*   | (0.084) |           | 0.006**   | (0.016) |
| edu square    | 0.016***  | (0.001) |           | −0.012***| (0.001) |           | 0.025***  | (0.000) |
| health        |           | 0.013*** | (0.007) |           | 0.006   | (0.124) |           | 0.010**   | (0.038) |
| Health*tech   |           | 0.01**   | (0.001) |           | 0.002   | (0.491) |           | 0.006**   | (0.017) |
| health square | −0.001*** | (0.000) |           | −0.001** | (0.000) |           | −0.001*** | (0.000) |
| tech          |           | −0.065   | (0.166) |           | 0.010   | (0.766) |           | −0.132*** | (0.008) |
| tech square   |           | 0.165*** | (0.000) |           | 0.019   | (0.589) |           | 0.202***  | (0.000) |
| female ratio  | 1.513    | (0.000) |           | 1.661*** | (0.000) |           | 1.985***  | (0.000) |
| Ln income     | −0.087*** | (0.000) |           | −0.07*** | (0.000) |           | −0.007    | (0.000) |
| disa          | −0.018*** | (0.000) |           | −0.022***| (0.000) |           | −0.003    | (0.000) |
| finance       | −0.056   | (0.607) |           | −0.177   | (0.071) |           | −0.026    | (0.000) |
| year          | 0.010***  | (0.000) |           | 0.005*** | (0.000) |           | −0.010    | (0.000) |
| cons          | 1.437***  | (0.000) |           | 0.577**  | (0.011) |           | −0.002    | (0.000) |
|               |           | 0.000    | (0.021) |           | 0.025   | (0.000) |           | 0.000     | (0.000) |
| N             | 435      | 435      | 435      | 435      | 435      | 435      | 435      | 435      | 435     |
| Wald chi²(18) | 4473.89  | 4342.80  | 4869.28  | 1314.33  | 1174.12  | 1318.86  | 2989.36  | 2573.57  | 2928.53 |
| Prob > chi²   | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   |
proportion of women in corn planting is, the higher the cost efficiency is. Only model (3) passed the 10% significance test.

**Analysis on the influence path of human capital on cost efficiency**

To further analyse the impact path of human capital on cost efficiency, this article takes technical efficiency and allocation efficiency as dependent variables, educational human capital, healthy human capital and technical human capital as core explanatory variables respectively, and constructs a model for regression. The results are shown in Table 9.

**The influence of human capital on technical efficiency**

From the results shown in Table 9, the impact of educational human capital on technical efficiency has passed the 1% significance test, and the regression coefficient is 0.198, which shows that it has a significant role in promoting technical efficiency. Regression coefficients are estimations of undetermined demographic features that characterise the connection among a regression model and a responder factor. The orientation of the association among a regression model and a responder factor is shown by the symbol of every statistic. However, its square term is significantly negative, which indicates that its impact on technical efficiency has an inverted ‘U’ shape. The cross item of educational human capital and technical human capital has a positive effect on technical efficiency, which indicates that educational human capital plays a positive role in promoting technical efficiency by improving technical human capital. It verifies the hypothesis that educational manpower can provide knowledge base for farmers’ skill learning. The impact of healthy human capital on technical efficiency is not significant. Although the square term of healthy human capital has passed the 10% significance test, the impact coefficient is small. Technical human capital did not pass the significance test. It can be seen that only educational human capital has a significant impact on technical efficiency.

Among the control variables, the impact of disaster area on cost efficiency is significantly negative, and the proportion of personal disposable income and agricultural financial expenditure is negative but unstable. The influence of female proportion on technical efficiency is not significant.

**The influence of human capital on allocation efficiency**

Human capital is defined as the pool of abilities, skills, besides personal characteristics contained in the capacity to execute labour as well as generate financial benefit. It refers to the skills and abilities acquired through a worker via education and experience. It is the process of gradually increasing the productive capacity of the economy. The results in Table 9 show that the regression coefficient of the impact of educational human capital on allocation efficiency is −0.346 at the 1% significant level, and the square regression coefficient is 0.006. It shows that there is a limit value of the influence of education level on allocation efficiency. As long as it exceeds this value, educational human capital will promote the improvement of allocation efficiency. The positive cross term of educational human capital and technical human capital indicates that educational human capital plays a positive role in allocation efficiency through technical human capital. Through the coefficient of healthy human capital and its square term, we can judge that the impact of healthy human capital on allocation efficiency is inverted ‘U’. It shows that healthy human capital can provide effective labour in the process of planting and form a reasonable allocation with other factors. However, if too much labour is provided, there will be labour surplus, which is not conducive to the rational allocation of factors and has a negative impact on the allocation efficiency. In addition, healthy human capital provides the basic guarantee for farmers to learn technology and promotes the positive impact of skill efficiency on allocation efficiency. The cross coefficient of the two is 0.006. Technical human capital and its square term are one negative and one positive at 1% significant level, which indicates that technical human capital has a positive ‘U’ effect on allocation efficiency. When corn farmers master certain skills, the more reasonable the allocation of factors in the process of corn planting, the more efficient the allocation can be. However, with the growing number of farmers mastering skills, in the face of interest driven, farmers are less willing to plant, more willing to engage in non-agricultural work to earn more income, and the allocation efficiency is reduced. Among the control variables, female proportion has a greater impact on allocation efficiency. It can be seen that with the increase of educational human capital and technical human capital, the improvement of the efficiency of progressive allocation is gradually obvious. Healthy human
capital has a certain number of restrictions on the improvement of cost efficiency.

**An empirical study on the impact of human capital on cost efficiency in different corn production areas**

**The impact of human capital on cost efficiency in different production areas**

To further analyse the differences and effects of human capital on cost efficiency in different main corn production areas, the main corn producing provinces in China are divided into five main corn production areas based on the division method of Yan-Hua and Li (2006). They are Northeast China (Liaoning, Jilin, Heilongjiang), North China (Hebei, Shanxi, Inner Mongolia), East China (Jiangsu, Anhui, Shandong, Henan), Southwest China (Sichuan, Yunnan) and Northwest China (Shaanxi, Gansu and Ningxia). Owing to the lack of data in some years in Guizhou and Xinjiang, the Southwest and Northwest regions are reduced to two and three provinces, respectively. This article uses the bidirectional fixed-effect model to measure the impact of human capital on cost efficiency in different production areas and the impact path. The results are shown in Table 10.

As shown in Table 10, the impact of educational human capital on cost efficiency is different. In Northeast, North and East China, the impact coefficient of educational human capital on cost efficiency is not significant, but its square has passed the significance test, and the impact coefficients are 0.019, 0.018 and 0.026, respectively. It shows that in the aforementioned three production areas, the role of farmers’ education level in cost efficiency is not fully apparent, but with the increase of farmers’ education level, it has a significant role in promoting cost efficiency. In the Southwest and Northwest regions, the impact of educational human capital on cost efficiency has not passed the significance test. However, in the northwest region, the cross-regression coefficient of educational human capital and technical human capital is 0.003 at the 1% significance test level, which indicates that educational human capital promotes cost efficiency through technical human capital. Healthy human capital has a significant positive effect on cost efficiency in the five major production areas, but the regression coefficient of its square term (except for East China) has not passed the significance test. The cross term of healthy human capital and technical human capital has a negative effect on cost efficiency. This is mainly related to the mode of corn planting in China. At present, corn planting in China is mainly small-scale artificial planting. Healthy human capital provides effective labour and saves the cost of using machinery. However, skilled farmers are more inclined to use modern planting methods to replace the traditional healthy artificial planting mode, and the interaction coefficient is negative. The influence of technical human capital on the cost efficiency of corn production areas is negative, but its square effect on the cost efficiency is significantly positive, especially in Northeast China, the regression coefficient is 0.567, which is significantly higher than the technical human capital itself. It shows that the influence of technical human capital on cost efficiency is positive ‘U’ type in the five production areas. Therefore, we should strengthen the training of technical manpower.

**Analysis on the influence path of human capital on cost efficiency in different production areas**

To further analyse the influence of human capital on the change of technical efficiency and allocation efficiency in different corn production areas, and explore the source of the influence of human capital on cost efficiency in different corn production areas, this article makes regression analysis on the technical efficiency and allocation efficiency in each corn production area, and the analysis results are shown in Table 10.

**The impact of human capital on technical efficiency in different production areas**

The impact of educational human capital on the technical efficiency of Northeast, North, East and Northwest corn production areas is significantly positive, passing the significance test of 1% and 5%, respectively, but the square coefficient is reduced. It shows that in the aforementioned four production areas, the higher the educational human capital is, the lower the planting willingness is, the less cultural knowledge is applied to corn planting and the less obvious the effect on improving the technical efficiency is. The regression coefficient of the cross items of educational human capital and healthy human capital in the four production areas is significantly negative. The influence coefficients of the cross items of educational human capital and technical human capital are positive, but the regression coefficient is small. It can be seen that in the aforementioned production areas, the higher the educational human capital is, the lower the impact on technical efficiency is.

In the Northeast, East and Northwest regions, the impact of healthy human capital on technical efficiency is more significant, respectively, through the
Table 10. Impact of human capital on cost efficiency and path analysis (by region).

| Production area       | Educational human capital | Technical human capital |
|-----------------------|---------------------------|------------------------|
|                       | edu | edu*health | edu*tech | edu sq | health | Health*tech | Health sq | tech | tech sq |
| Northeast China CE    | -0.143 | 0.014 | 0.002*** | 0.019* | 0.0685*** | -0.003*** | 0.004 | -0.468*** | 0.567*** |
|                       | (0.381) | (0.197) | (0.005) | (0.082) | (0.000) | (0.000) | (0.507) | (0.000) | (0.000) |
|                      | TE  | 0.252** | -0.016* | 0.000 | 0.018*** | 0.024** | -0.002** | 0.013** | 0.030 | 0.086 |
|                       | (0.039) | (0.054) | (0.637) | (0.000) | (0.020) | (0.022) | (0.012) | (0.743) | (0.359) |
| North China CE        | -0.321** | 0.026*** | 0.002*** | -0.000 | 0.056*** | -0.003*** | -0.005 | -0.501*** | 0.544*** |
|                       | (0.015) | (0.064) | (0.000) | (0.957) | (0.000) | (0.000) | (0.400) | (0.000) | (0.000) |
|                       | (0.846) | (0.586) | (0.000) | (0.009) | (0.000) | (0.033) | (0.141) | (0.011) | (0.000) |
|                      | TE  | 0.380*** | -0.026** | 0.001* | 0.011*** | 0.017 | -0.001 | 0.015** | 0.076 | 0.052 |
|                       | (0.002) | (0.002) | (0.060) | (0.000) | (0.107) | (0.242) | (0.003) | (0.398) | (0.581) |
| East China CE         | -0.305** | 0.025*** | 0.023*** | 0.005 | 0.046*** | -0.002*** | -0.000 | -0.414*** | 0.476*** |
|                       | (0.028) | (0.008) | (0.000) | (0.417) | (0.000) | (0.028) | (0.938) | (0.000) | (0.000) |
|                       | (0.455) | (0.240) | (0.000) | (0.000) | (0.000) | (0.000) | (0.035) | (0.081) | (0.004) |
|                      | TE  | 0.261** | -0.017** | 0.001 | 0.022*** | 0.027** | -0.002** | 0.016*** | 0.105 | 0.034 |
|                       | (0.036) | (0.049) | (0.213) | (0.000) | (0.011) | (0.021) | (0.002) | (0.282) | (0.729) |
|                      | ATE | -0.317** | 0.026*** | 0.003*** | 0.011 | 0.064*** | -0.003*** | 0.004 | -0.339*** | 0.413*** |
|                       | (0.017) | (0.004) | (0.000) | (0.054) | (0.000) | (0.000) | (0.483) | (0.002) | (0.000) |
| Southwest China CE    | -0.215 | 0.016 | 0.001 | 0.003 | 0.052*** | -0.003*** | 0.004 | -0.277*** | 0.341*** |
|                       | (0.209) | (0.177) | (0.247) | (0.680) | (0.000) | (0.001) | (0.880) | (0.025) | (0.009) |
|                      | TE  | 0.091 | -0.007 | -0.000 | 0.015*** | 0.019* | -0.001** | 0.013*** | 0.179* | -0.079 |
|                       | (0.461) | (0.425) | (0.327) | (0.004) | (0.058) | (0.018) | (0.007) | (0.046) | (0.398) |
|                      | ATE | -0.299** | 0.022*** | 0.001** | -0.008 | 0.042*** | -0.002*** | -0.009** | -0.429*** | 0.423*** |
|                       | (0.025) | (0.017) | (0.033) | (0.138) | (0.000) | (0.001) | (0.086) | (0.000) | (0.000) |
| Northwest China CE    | 0.050 | 0.010 | 0.003*** | 0.013 | 0.059*** | 0.002*** | 0.0018 | -0.355** | 0.425** |
|                       | (0.761) | (0.767) | (0.000) | (0.116) | (0.000) | (0.005) | (0.826) | (0.016) | (0.003) |
|                      | TE  | 0.330*** | -0.019** | 0.001** | 0.007 | 0.027*** | -0.001** | -0.005 | -0.158 | 0.178* |
|                       | (0.003) | (0.010) | (0.020) | (0.244) | (0.005) | (0.034) | (0.930) | (0.104) | (0.055) |
|                      | ATE | -0.185 | 0.018* | 0.002*** | 0.007 | 0.045*** | -0.002** | 0.004 | -0.295** | 0.345*** |
|                       | (0.164) | (0.052) | (0.000) | (0.276) | (0.000) | (0.011) | (0.947) | (0.014) | (0.003) |

5% and 1% significance test, the regression coefficients are about 0.03. The regression coefficient of the square term of healthy human capital is lower than that of the first term, and the impact of healthy human capital on technical efficiency shows an inverted ‘U’ shape. This shows that the planting patterns in Northeast, North and Northwest China are still dominated by artificial planting, and the effective labour force makes a greater contribution to the technical efficiency. But if it exceeds a certain amount of labour supply, it will cause the decline of technical efficiency. For the Southwest region, the regression coefficient of healthy human capital on technical efficiency is 0.019. Through the 10% significance test, it shows that the impact is not significant enough.

The impact of technical human capital on technical efficiency is only significant in Southwest production areas, the regression coefficient is 0.179, passing the 5% significance test. In this production area, technical human capital increased by 1-unit, technical efficiency increased by 0.179 units. The effect of technical human capital on technical efficiency is not significant in other regions. This shows that only in the southwest region, the skill level of farmers engaged in corn planting is higher. In other production areas, skilled farmers tend to go out to work and earn more wages, rather than engage in corn cultivation.

Therefore, in Northeast, North and Northwest China, educational human capital and healthy human capital play a positive role in promoting technical efficiency. But both of them have a certain optimal value and cannot be increased without limit. Technical human capital plays a significant positive role in technical efficiency in Southwest China.

The impact of human capital on allocation efficiency in different production areas

The allocation efficiency of educational human capital to Northeast, North, East and Southwest regions have a negative correlation at the 5% significant level, the regional difference is not big, and the influence coefficient is about 0.3. It shows that every unit of human capital increase, the allocation efficiency of each production area decreases by 0.3 units on average. In the Northwest region, the impact of educational human capital on allocation efficiency is not significant. However, the cross items of education capital and healthy human capital and education capital and technical human capital all pass the significance test, and the influence coefficient is positive. It shows that educational human capital itself has little effect on allocation efficiency, mainly through healthy human capital and educational human capital. Among them, North China is the most significant area, and the influence...
coefficients are 0.025 and 0.023, respectively, which are significant at the level of 1%.

The impact of healthy human capital on the allocation efficiency of the five production areas is not significant, and it has a positive effect at 1% significant level. Among them, it has the greatest impact on the allocation efficiency of East China, with the impact coefficient of 0.064, followed by Northeast, North, Northwest and Southwest China. However, the cross item of healthy human capital and technical human capital has a significant negative effect on allocation efficiency. It shows that healthy labour force can provide farmers with good learning skills, but technical human capital reduces the allocation efficiency because of brain drain. According to the current situation of human capital, healthy human capital aggravates the loss of allocation efficiency through technical human capital.

The effect of technical human capital on allocation efficiency is significantly negative in each production area, but its square term is significantly positive. It shows that with the increase of the number of skill training, the promotion of allocation efficiency will increase.

**Endogenous problems**

The fundamental issue of individual heterogeneity arises whenever the explanans (X) can be impacted by the collection period (Y), and whenever both can be changed concurrently through an unquantified party. The explanatory variables issue is one element of the wider issue of adverse selection, which was previously explored. The explanatory variables used in this article are provincial panel data, which reflect the overall situation of rural areas in each province, rather than the data for corn crops. There are errors in measurement. In addition, the control variables did not take into account environmental factors, there are missing variables, this leads to the endogeneity problem of the model and the overestimation of the calculation results.

**Limitations**

Enhancing cost efficiency is one among the most important strategies to minimise agricultural product manufacturing costs as well as enhances farmer revenue. Human capital is an essential approach to increase cost efficiency since it is a ‘whole system participant’ in addition to ‘decision maker’ in the manufacturing process. The majority of current literatures are concerned with the relationship between humans’ capital and agricultural productivity improvement else agriculture economic expansion. The examination of intellectual capital's role is neither thorough nor in-depth.

**Conclusions and suggestions**

Improving agricultural cost efficiency is an important means to reduce agricultural production costs, which is related to the vital interests of farmers. Human capital is an important way to improve agricultural cost efficiency. To better play the role of human capital in the promotion of agricultural cost efficiency, it is necessary to determine the impact of human capital on cost efficiency and the path of action. This article takes the main corn production areas in China as an example to verify the role of human capital in cost efficiency from three dimensions of educational human capital, healthy human capital and technical human capital. The differences among the five main maize production areas were compared. The main conclusions are as follows:

1. On the whole, the impact of educational human capital on cost efficiency presents a positive ‘U’ shape. The impact of Northeast, North and East China is similar to that of the whole, but it is not significant in Northwest China. Education capital mainly acts on cost efficiency by promoting technical efficiency and allocation efficiency.

2. Healthy human capital plays a positive role in promoting cost efficiency, but with the increase of healthy human capital, its role will gradually weaken. This effect is more obvious in all production areas except Southwest China. There is an optimal allocation ratio between healthy human capital and cost efficiency. The impact of healthy human capital on cost efficiency is mainly realised through the path of allocation efficiency.

3. The effect of technical human capital on cost efficiency shows a positive ‘U’ type change, and the change of each production area is the same as that of the whole. Technical human capital affects cost efficiency mainly through the path of allocation efficiency.

All production areas should increase the education level of farmers, especially the northwest production areas should actively develop farmers’ education and improve their education level. Each production area should encourage healthy farmers to provide appropriate agricultural labour according to family conditions, and disperse surplus labour force, so as to avoid excessive labour input, improper factor input and low-cost
efficiency. Local governments should vigorously promote skills training for farmers, especially in Northeast China, where the potential of technical human capital is huge.

Disclosure statement
No potential conflict of interest was reported by the author(s).

Notes on contributors
Wang Qian (1983 -), female, born in Fushun, Liaoning Province, China, is a doctoral candidate in school of economics and management, Shenyang Agricultural University. She also is a teacher at Shenyang Institute of Technology. She is mainly engaged in the research of agricultural industrial organization and management and agricultural economic theory and policy.

Lu Jie (1963 -), male, born in Suzhou, Anhui Province, China, is a professor and doctoral supervisor of School of economics and management of Shenyang Agricultural University. He is mainly engaged in agricultural development, agricultural modernization and agricultural economic theory and policy research.

References
Ahmed MH, Melesse KA. 2017. Impact of off-farm activities on technical efficiency: evidence from maize producers of eastern Ethiopia. Agric Food Econ. 5(1):1–20.

Banker RD, Charnes A, Cooper WW. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage Sci. 30(9):1078–1092.

Battese GE, Coelli TJ. 1995. A model for technical inefficiency effects in stochastic frontier production function for panel data. Empir Econ. 20(2):325–332.

Deepa N, Khan MZ, Prabadevi B, et al. 2020. Multiclass model for agricultural development using multivariate Statistical method. IEEE Access. 8:183749–183758.

Farrell MJ. 1957. The Measurement of economic efficiency. J R Stat Soc. 120(3):253–290.

Gao J, Wang H, Shen H. 2020. Machine learning based workload prediction in Cloud computing. 2020 29th International conference on computer communications and networks (ICCCN).

Jianhua W. 2011. Study on cost efficiency of crops and regional characteristics based on DEA-Taking Soybean for example. Econ Geogr. 31(7):1190–1195.

Jingbo L, Yuan G. 2020. Research on the influence mechanism of China’s population aging on labor productivity. NanKai Econ Stud. (03):61–80.

Luther GC, Mariyono J, Purnagunawan RM, et al. 2018. Impacts of farmer field schools on productivity of vegetable farming in Indonesia. Nat Resour Forum. 42(2):71–82.

Mankiw NG, Romer D, Well DN. 1992. A contribution to the empirics of Economic growth. Q J Econ. 107(2):407–437.

Manogaran G, Hsu C, Rawal BS, et al. 2021. ISOF: information shedding and optimization framework for improving the performance of agricultural Systems aided by industry 4.0. IEEE Internet Things J. 8(5):3120–3129.

Mariyono J. 2014. Rice production in Indonesia: policy and performance. Asia Pac J Public Adm. 36(2):123–134.

Mariyono J. 2019. Farmer training to simultaneously increase productivity of soybean and rice in Indonesia. Int J Product Perform Manag. 68(6):1120–1140.

Miller SM, Upadhyay MP. 2000. The effects of openness trade orientation and human capital on total factor productivity. J Dev Econ. 63(2):399–423.

Mukherjee DN, Vasudev N, Vijaya Kumari R, Suhasini K. 2017. Estimation of total factor productivity and its determinants of maize in Telangana state. Econ Aff. 62(4):595–601.

Nieto Y, García-Díaz V, Montenegro C, et al. 2019. Ecocolonel usage of machine learning for strategic decision making at higher educational institutions. IEEE Access. 7:75007–75017.

Ojo OM, Adenuga AH, Lauwers L, Van Meensel J. 2020. Unraveling the impact of variable external input use on the cost efficiency of dairy farms in Europe. Environ Sustainability Indic. 8:100076.

Orjuela KG, Gaona-Garcia PA, Marin CE. 2020. Towards an agriculture solution for product supply chain using block chain: case study agro-chain with BigchainDB. Acta Agric Scand Sect B. 71(1):1–16.

Oumer AM, Michael B, Atakelly H, Amin M. 2020. Sustainable agricultural intensification practices and cost efficiency in smallholder maize farms: evidence from Ethiopia. Agric Econ. 51(6):841–856.

Phillips JM, Marble RP. 1986. Farmer education and efficiency: a frontier production function approach. Econ Educ Rev. 5 (3):257–264.

Quixia Y, Zhaojiu C, Huiting X. 2018. Labor allocation efficiency of farmer households and its influencing factors: based on the survey data of 637 farmer households in Jiangxi province. J Hunan Agric Univ (Soc Sci). 19(5):11–18.

Sanusi SM, Singh IP. 2016. Empirical analysis of economies of scale and cost efficiency of small-scale Maize Production in Niger state, Nigeria. Indian J Econ Dev. 12(1):55–64.

Saravanan V, Pralhaddas KD, Kothari DP, et al. 2015. An optimizing pipeline stall reduction algorithm for power and performance on multi-core CPUs. Hum-centric Comput Inf Sci. 5 (2).

Schultz TW. 1961. Investment in human capital. Am Econ Rev. 51(1):1–17.

Shengli Y, Shijiang D. 2016. The study of efficiency of labor resource allocation in China. Hum Resour Dev Int. 19:71–79.

Wei S, Gucheng LI, Xue GAO. 2018. Study on regional differences and influencing factors of maize cost efficiency: based on the survey data of 17 main producing province in 2004-2015. J Hunan Agri Univ (Soc Sci). 19 (2):8–15.

Wei Y, Peng Z, Zhiheng J. 2020. Spatial interaction effect of rural education human capital and agricultural total factor productivity in China—empirical analysis based on spatial simultaneous equations. J China Agric Univ. 25 (03):192–202.

Xiaochen Z. 2020. Research on the efficiency of rural human capital on agricultural total factor productivity[D]. Zhejiang City: ZheJiang University of Finance and Economics.

Xiaoshi Z, Gucheng L, Cheng L, Capital H. 2018. Land scale and agricultural production efficiency. J Huazhong Agri Univ (Soc Sci Ed). (2):8–18.
Xiao-Yong X, Qiu-Ping L. 2012. Education, health and efficiency of agricultural production-based on positive study of provincial panel data between 1999–2009[J]. J Huazhong Agric Univ. (3):48–53.

Xuejiao W, Haifeng X. 2016. Spatial correlation measurement and influence factors of allocation efficiency for maize production in China. J HIT (Soc Sci Edi). 18(6):125–131.

Yan-Hua Z, Li L. 2006. Empirical analysis on contribution of rural human capital to rural economic growth. J Cent Univ Fin Econ. 8:61–65.

Yuqiu W, Lei L. 2016. The influence of New rural cooperative medical insurance and health human capital on labor participation of rural residents. China’s Rural Econ. 11:68–81.