Hindawi
Complexity
Volume 2019, Article ID 9190273, 11 pages
https://doi.org/10.1155/2019/9190273

Research Article

Analysis of Financing Efficiency of Chinese Agricultural Listed Companies Based on Machine Learning

Lixia Liu [1] **and Xueli Zhan** [2]

[1] *School of Economics, Tianjin University of Commerce, Tianjin 300134, China*
[2] *School of Economics, Beijing Wuzi University, Beijing 101149, China*

Correspondence should be addressed to Lixia Liu; liulixia77@163.com and Xueli Zhan; xuelz20163205@126.com

Received 4 April 2019; Revised 14 June 2019; Accepted 24 June 2019; Published 10 July 2019

Guest Editor: Benjamin M. Tabak

Agricultural enterprises play a significant role in China's economic development. However, compared with other enterprises, agricultural enterprises are facing serious financial problems. Financing difficulty is essentially a question of financing efficiency. Based on the DEA method, this paper evaluates the financing efficiency of 39 agricultural listed companies in China from 2013 to 2017. The results suggest that the financing efficiency is generally low, and the Total Factor Productivity of agricultural enterprises' financing has a tendency to decrease first and then increase. The influencing factors of financing efficiency are analyzed using the Tobit regression model and the random forest regression model. And we find the following: (1) The random forest regression model significantly outperformed the Tobit regression model, with determination coefficients (R^2) greater than 0.9 in full sample sets. (2) Total liability, financial expenses, return on total assets, and inventory turnover rate are important factors affecting financing efficiency of agricultural listed companies. (3) Return on total assets and inventory turnover rate promote the financing efficiency, while total liability and financial expenses reduce financing efficiency. Finally, the paper makes some suggestions for the financing of agricultural enterprises.

1. Introduction

Agriculture not only provides us with the food and clothing, but also provides us with energy and chemical raw materials needed for industrial development. It is a basic industry related to economic development and social stability. Agricultural enterprises are the most important organizations in modern agricultural industrial system and the important bridge connecting farmers and the market. Agricultural enterprises are more difficult to operate than other enterprises, particularly in developing countries such as China [1]. They are not only affected by social factors, but also affected by natural factors, especially the weather. Under the influence of severe weather, the agricultural enterprises may be subjected to uncontrollable factors, which can increase the risk of corporate failure and default [2]. So, agricultural enterprises often face more severe financing problems [3]. Public sector funding is widely believed to be a more effective measure for agricultural progress [4]. However, government funds are often limited. It is essential to enhance the external financing capacity and financing efficiency of agricultural enterprises. The research on agricultural financing mainly focuses on financing structure, financing mode, and agricultural financial policy [5–12]. Abate et al. [6] analyzed the impact of institutional finance on agricultural technology adoption in Ethiopia, and the results showed that the access to institutional finance had a significant positive impact on farmers' adoption of agricultural technology. However, few scholars pay attention to the financing efficiency of agricultural enterprises.

Financing efficiency is a key index to estimate an enterprises' efficiency of using their funds. From the literature, we note that the research on the enterprises' financing efficiency can be divided into three perspectives including regions [13, 14], industries [15–17], and capital market [18, 19]. Geng et al. [13] evaluated the financing efficiency of listed companies of machinery manufacturing industry in Jiangsu based on the Malmquist index model. Ma et al. [17] analyzed the

financing efficiency of 21 listed companies in LED lighting industry in photovoltaic industry, and the results indicated that the financing efficiency showed an upward trend, but the overall level was low. Dong et al. [18] analyzed the financing efficiency of 300 listed companies in Shanghai and Shenzhen Stock Exchange from 2008 to 2014, and the results showed that the financing efficiency of Chinese listed companies was generally low. Data envelopment analysis (DEA) first proposed by Charnes et al. is a common method used to evaluate financing efficiency [20]. Compared with other methods, the DEA method has many advantages: there is no need to estimate the production function, it is capable of handling multiple inputs and outputs, and it is capable of analyzing the reasons for the inefficiency of each evaluation unit. Prior studies also investigated the impact of internal and external factors on the enterprises' financing efficiency. The internal factors mainly include capital structure, financing cost, financing mode, property nature, firm age, and firm size [21–25]. The external factors mainly include macroeconomic situation, financial development, external financial support, legal environment, market competition, and interfirm trust [26–29]. The linear regression model has been the most commonly used method in the analysis of influencing factors of financing efficiency. With the development of computer technology, the application of machine learning and game theory in the economic field has gradually increased, but research in the field of corporate finance is still rare [30–33].

This paper selects 39 agricultural listed companies in Shanghai Stock Exchange and Shenzhen Stock Exchange from 2013 to 2017, evaluates financing efficiency of Chinese agricultural listed companies with DEA model, and explores the impact of internal and external factors on financing efficiency. We contribute to the existing literature on enterprises' financing efficiency in three respects. First, we focus purely on agricultural enterprises and hope this research can help to improve the overall level of agricultural enterprises' financing efficiency. Numerous researches have focused on the financing efficiency of regions, industries, and capital market. So far, there are relatively few studies on the financing efficiency of agricultural enterprises [29]. Second, we calculate the financing efficiency of agricultural listed companies in China's Stock Market. China's agricultural enterprises are a significant case study for our purposes. China is a big agricultural country with abundant agricultural resources, a long history of agriculture, and a huge rural population. Now, more than 20% of the Chinese population still lives on farms. In 2016, the number of agricultural industrialization organizations in China had reached 417,000, an increase of 8.01% over 2015. Agricultural industrialization is the development direction of China's agriculture, and the development of agricultural enterprises is related to the long-term development of China's agriculture. Our third contribution is methodological. In recent years, the methods such as game theory and machine learning have been applied more and more in the field of economics, but few people apply them to the analysis of financing efficiency [34–37]. Random forest is an ensemble machine learning methods of classification and regression proposed by Leo Breiman [38]. It has proven to be an effective analytical tool for studying the relationship between predictors and response because of its excellence in interpretation, visualization, and abilities to handle complex nonlinearity [39–41]. The random forest regression model is used to explore the impact of internal and external factors on financing efficiency, and the results are compared with those of econometric regression analysis. The paper not only provides examples of application of machine learning methods on the research field of financing efficiency, but also has practical significance for empirical analysis on the financing efficiency of Chinese agricultural listed companies.

The rest of this paper is organized as follows. Section 2 introduces the models used throughout this paper. Section 3 describes the key variables and the data source. Section 4 provides the empirical results and discussion, which include the evaluation of financing efficiency of agricultural enterprises and study of its antecedents. The conclusion and policy suggestions are given in Section 5.

2. Methods

2.1. DEA Model. Data Envelopment Analysis (DEA) introduced by Charnes et al. [20] is a nonparametric method to measure relative efficiency of the analyzed objects with multiple inputs and multiple outputs. Different from other measuring efficiency methods, DEA model treats the DMU as a "black box." We don't need to determine the functional relationship between input and output metrics before using the DEA model. The method introduces linear programming to construct nonparametric piecewise surfaces of observed data and then computes efficiency relative to this frontier.

According to these assumptions, DEA model can be divided into two categories: constant return to scale (CRS) and the variable return to scale (VRS). VRS is an improvement to the CRS model, which is used to explain the variable scale income. When the enterprise is not satisfied with the optimal scale operation, VRS can avoid the confusion between the measurement result of the technical efficiency and scale efficiency. Obviously, we should use the VRS model to study agricultural enterprises' financing efficiency.

Suppose that there are I decision making units (DMUs), and each decision making unit has N inputs and M outputs. Let $X_i = (x_{1i}, x_{2i} \cdots x_{Ni})^T$ and $Y_i = (y_{1i}, y_{2i} \cdots y_{Mi})^T$ be the input vector and the output vector of DMUs I, respectively. The $N \times I$ input matrix and the $M \times I$ output matrix Y represent the data of all I decision making units. The DEA model can be shown as follows:

$$\begin{aligned} \min \quad & \theta \\ \text{s.t.} \quad & \sum_{i=1}^{n} \lambda_i x_i - \theta x_0 \leq 0 \\ & \sum_{i=1}^{n} \lambda_i y_i - x_0 \geq 0 \\ & \lambda_i \geq 0 \end{aligned} \tag{1}$$

where θ denotes the efficiency score of DMU i and λ denotes the weight of DMUi. When the decision unit θ is equal to 1,

the DMU is efficient; i.e., its inputs and outputs have reached optimal combination in the production system.

2.2. Malmquist Index Model. Malmquist [41] firstly proposed the Malmquist index and used this method to analyze the consumption behavior. Based on Malmquist's work, Caves et al. [42] put forward the Malmquist productivity index in 1982. The Malmquist productivity index is an effective method of measuring Total Factor Productivity (TFP). The Malmquist productivity index from t period to t+1 can be written as follows:

$$M\left(x^t, q^t, x^{t+1}, q^{t+1}\right) = \left(\frac{D^t\left(x^{t+1}, q^{t+1}\right)}{D^t\left(x^t, q^t\right)} \times \frac{D^{t+1(x^{t+1}, q^{t+1})}}{D^{t+1}\left(x^t, q^t\right)}\right)^{1/2} \quad (2)$$

where x^t, q^t are the input and output vector of period t, respectively. $D^t(x^t, q^t)$ and $D^{t+1}(x^t, q^t)$ denote the distance function of the DMU of period t and t+1 when the period *t* is taken as reference.

Färe et al. [43] improved the model and decomposed Total Factor Productivity (TFP) into efficiency change (EC) and technical change (TC). The formulas are stated as follows:

$$M\left(x^t, q^t, x^{t+1}, q^{t+1}\right) = \frac{D^{t+1(x^{t+1}, q^{t+1})}}{D^t\left(x^t, q^t\right)} \times \left(\frac{D^t\left(x^{t+1}, q^{t+1}\right)}{D^{t+1(x^{t+1}, q^{t+1})}} \times \frac{D^t\left(x^t, q^t\right)}{D^{t+1}\left(x^t, q^t\right)}\right)^{1/2} \quad (3)$$

$$EC = \frac{D^{t+1(x^{t+1}, q^{t+1})}}{D^t\left(x^t, q^t\right)} \quad (4)$$

$$TC = \left(\frac{D^t\left(x^{t+1}, q^{t+1}\right)}{D^{t+1(x^{t+1}, q^{t+1})}} \times \frac{D^t\left(x^t, q^t\right)}{D^{t+1}\left(x^t, q^t\right)}\right)^{1/2} \quad (5)$$

The rate of technical change (TC) can be divided into pure technical efficiency change (PTEC) and scale efficiency change (SEC). The formulas are shown as follows:

$$PTEC = \left(\frac{D^t\left(x^{t+1}, q^{t+1}\right)}{D^{t+1(x^{t+1}, q^{t+1})}}\right)^{1/2} \quad (6)$$

$$SEC = \left(\frac{D^t\left(x^t, q^t\right)}{D^{t+1}\left(x^t, q^t\right)}\right)^{1/2} \quad (7)$$

2.3. Tobit Regression Model. The value of financing efficiency is between 0 and 1, which is the truncated data. When we use financing efficiency as a dependent variable to analyze the effect of various factors on financing efficiency, there may be biased and inconsistent estimating results by ordinary linear regression. Tobit regression model, also called a censored regression model, is designed to estimate linear relationships between variables when there is either left or right censoring in the dependent variable [44]. So we can use this method to resolve the above problems. The model is shown as follows:

$$y_i = \begin{cases} 0 & if\ y_i^* \le 0 \\ \beta x_i{}' + \varepsilon_i & if\ 0 < y_i^* < c \\ c & if\ y_i^* \ge c \end{cases} \quad (8)$$

where y_i is the dependent variable, y_i^* is the latent variable, $x_i{}'$ is the independent variables, β is the parameter vector, and $\varepsilon_i \sim N(0, \sigma^2)$ is a random perturbation.

2.4. Random Forest Regression Model. Random forest is a wonderful machine learning approach which is used for classification and regression as an ensemble learning [38]. It contains several decision trees trained by bootstrap resampling method. When a sample to be regressed is entered, the final regression result is determined by the vote of the output of these decision trees. Random forest overcomes the problem of overfitting and has good tolerance to noise and anomaly values. It is a fully nonparametric statistical method that optimizes predictive accuracy by fitting an ensemble of trees to stabilize model estimates.

The steps to generate a random forest can be represented as follows:

(1) The bootstrap resampling method is applied to randomly extract *k* samples from the original training sets, and then *n* regression trees are generated.

(2) For each of the bootstrap samples, an unpruned regression tree is grown. At each node, m of the predictors are chosen randomly and the best split is chosen among those predictors.

(3) Predict new data by aggregating the predictions of the *n* trees (i.e., average for regression).

The mean square error (MSE) and the decision coefficient (R^2) are used as criteria for evaluating the model error. The calculation formulas are as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i'\right)^2 \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i'\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \quad (10)$$

where y_i is the actual value of dependent variable, y_i' is the predictive value of dependent variable, and $\overline{y}$ is the mean value of the dependent variable.

3. Indicator Selection and Data Sources

3.1. Financing Efficiency Evaluation Variables. The selection of optimum indicators is the hinge of analyzing the financing efficiency of agricultural listed companies using the DEA model. In this paper, we select total assets, operating cost, and equity ratio as the input indicators and select asset turnover ratio, earnings per share, and rate of return on common stockholders' equity (ROE) as output indicators.

(1) Total assets (X_1). The total assets are an indicator reflecting the financing ability of the enterprise. It's generally believed that the larger the total assets of the enterprise are, the larger the scale of the enterprise is, and the stronger the financing ability of the enterprise is.

(2) Operating cost (X_2). Operating cost refers to the costs associated with a company's main operating activities. The indicator can be used to indicate the use of corporate funds. As a rule, the higher the operating cost of the enterprise is, the higher the capital use cost of enterprise is.

(3) Equity ratio (X_3). Equity ratio is the ratio of the total liabilities to owner's equity. It is an important indicator for evaluating the rationality of capital structure. The lower the enterprise's equity ratio is, the stronger its long-term solvency is.

(4) Asset turnover ratio (Y_1). Asset turnover measures the efficiency ratio with which a company uses its assets to generate sales. It can be used as an indicator for evaluating the management quality and utilization efficiency of enterprise assets.

(5) Earnings per share (Y_2). Earnings per share are a financial ratio, which measures net earnings earned per share of stock outstanding. The larger the earnings per share are, the stronger the enterprise's equity financing ability is.

(6) Rate of return on common stockholders' equity (Y_3). Rate of return on common stockholders' equity is computed by dividing net income after interest, taxes, and preferred dividends to average common stockholders' equity. The higher the rate of return on common stockholders' equity ratio is, the higher the return of investors is, and the stronger the enterprise's profitability is. This indicator can be used to reflect the efficiency of the enterprise in using its own capital.

The values of the selected indicators are supposed to be positive in the DEA model, but some values selected in this paper are negative, so the data needs to be dimensionless. The approach is listed as follows:

$$Z_i' = 0.9 * \frac{(Z_i - \min(Z_i))}{(\max(Z_i) - \min(Z_i))} + 0.1 \tag{11}$$

where $i = 1, 2 \cdots, 6$, $\min(Z_i)$ and $\max(Z_i)$ are the minimum and maximum values of each variable, respectively.

3.2. Regression Variables. The multiple linear regression models are established in (12). In this paper, the dependent variable is financing efficiency calculated by the DEA model. Total liability, financial expense, return on total assets, inventory turnover rate, price index of agricultural means of production, and gross domestic product (GDP) are selected to investigate the effect of these factors on the financing efficiency of agricultural enterprises.

(1) Total liability (TL). Total liability refers to the aggregate debt for which agricultural enterprises are liable. Debt management is the most important means of agricultural enterprises' operation. It can alleviate agricultural enterprises' financing difficulties, expand their production scale, improve their market competitiveness, and promote their rapid development, while, when the total liabilities are too high, agricultural enterprise will face more financial risk.

(2) Financial expense (FE). Financial expenses refer to the expenses incurred by the enterprise in order to raise the funds needed for its operation. It is an indicator used to reflect the cost of enterprises to raise funds. Generally, the higher the financial expenses are, the higher the enterprises' financing cost is.

(3) Return on total assets (RT). Profitability is a measure of the enterprise's ability to pay off debts. Strong profitability means that the enterprises can get better returns and be able to repay their debts on time [45]. Thus, profitability is an indirect factor affecting the financing efficiency of enterprise. The indicators reflecting enterprises' profitability include gross profit margin, net profit margin, return on net assets, return on total assets, and earnings per share. Return on total assets is an important indicator of listed companies, which can reflect the efficiency of enterprises' asset operation and evaluate the ability of enterprise to manage assets.

(4) Inventory turnover rate (ITR). The indicator of turnover rate is usually used to indicate the operating efficiency of enterprise, including accounts receivable turnover rate, inventory turnover rate, current assets turnover rate, fixed asset turnover rate, and total asset turnover rate. The inventory turnover rate is an important indicator for measuring how efficiently a firm turns its inventory into sales. Generally, the higher the inventory turnover rate is, the lower the inventory occupancy level is, and the stronger the liquidity is, which will enhance the short-term solvency and profitability of the enterprise.

(5) Price index of agricultural means of production (PI). The price index of agricultural means of production measures changes in the price level of agricultural production materials. The agricultural production means mainly include agricultural hand tools, feed, animal products, semimechanized farm tools, mechanized farm tools, and so on. The higher the price of agricultural means of production is, the higher the market demands for agricultural enterprises' products are, and the higher the profitability of agricultural enterprises is.

(6) Gross domestic product (GDP). GDP is the total value of all the final goods and services produced within a country's borders in a specific time period. It is often used as an indicator for measuring the economic situation of a country.

To satisfy the requirement of stationarity, the explanatory variables of total liability, financial expenses, and GDP are logarithmically transformed. The factors are standardized by taking natural logarithms. The model of the effect of influence factors on the financing efficiency of agricultural enterprises is as follows:

$$\begin{aligned} \mathrm{TE} = {} & \beta_0 + \beta_1 \ln(\mathrm{TL}) + \beta_2 \ln(\mathrm{FE}) + \beta_3 \mathrm{RT} + \beta_4 \mathrm{ITR} \\ & + \beta_5 \mathrm{PI} + \beta_6 \ln(\mathrm{GDP}) + \varepsilon \end{aligned} \tag{12}$$

where TE is the values of comprehensive technical efficiency (TE) of agricultural enterprises' financing calculated by DEA model, β_0 denotes the intercept term, $\beta_1, \beta_2, \beta_3, \ldots, \beta_6$ represent the regression coefficients of variables, and ε is the residual term of the regression model. Since financial expenses involve negative numbers, in order to facilitate the logarithm, financial expenses are translated as follows:

$$\mathrm{FE}_i = \mathrm{Fe}_i + \min(|\mathrm{Fe}|) \tag{13}$$

where Fe_i denotes the original value of financial expenses, and FE_i represents the translated values of financial expenses.

3.3. Data Sources. We select agricultural listed companies in China from 2013 to 2017. In the selection process, the enterprises that have been given special treatment by the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SSE) or lack the selected variables values are excluded. Finally, we choose 39 enterprises as our sample. The information of 39 agricultural listed companies is shown in Table 1. The data are mostly derived from Wind Financial Terminal (http://www.eastmoney.com) and China Statistical Yearbook.

Table 1: 39 agricultural listed companies.

No	Stock code	Stock market
1	000592	Shenzhen Stock Exchange
2	000735	Shenzhen Stock Exchange
3	000798	Shenzhen Stock Exchange
4	000998	Shenzhen Stock Exchange
5	002041	Shenzhen Stock Exchange
6	002069	Shenzhen Stock Exchange
7	002086	Shenzhen Stock Exchange
8	002200	Shenzhen Stock Exchange
9	002234	Shenzhen Stock Exchange
10	002299	Shenzhen Stock Exchange
11	002321	Shenzhen Stock Exchange
12	002458	Shenzhen Stock Exchange
13	002477	Shenzhen Stock Exchange
14	002679	Shenzhen Stock Exchange
15	002696	Shenzhen Stock Exchange
16	002714	Shenzhen Stock Exchange
17	002746	Shenzhen Stock Exchange
18	002772	Shenzhen Stock Exchange
19	200992	Shenzhen Stock Exchange
20	300087	Shenzhen Stock Exchange
21	300094	Shenzhen Stock Exchange
22	300106	Shenzhen Stock Exchange
23	300189	Shenzhen Stock Exchange
24	300511	Shenzhen Stock Exchange
25	300761	Shenzhen Stock Exchange
26	600097	Shanghai Stock Exchange
27	600108	Shanghai Stock Exchange
28	600257	Shanghai Stock Exchange
29	600313	Shanghai Stock Exchange
30	600354	Shanghai Stock Exchange
31	600359	Shanghai Stock Exchange
32	600371	Shanghai Stock Exchange
33	600467	Shanghai Stock Exchange
34	600506	Shanghai Stock Exchange
35	600540	Shanghai Stock Exchange
36	600598	Shanghai Stock Exchange
37	600965	Shanghai Stock Exchange
38	600975	Shanghai Stock Exchange
39	601118	Shanghai Stock Exchange

4. Empirical Analysis

4.1. Descriptive Statistics. Before analyzing the financing efficiency of agricultural listed companies, descriptive statistics of the relevant variables will be discussed. Table 2 presents descriptive statistics regarding of all agricultural listed companies and macroeconomic indicators.

4.2. Measurement of Financing Efficiency Based on DEA Model. The financing efficiency of agricultural listed companies in China from 2013 to 2017 is measured by using DEA model. The results are shown in Table 3. We can see that the financing efficiency of agricultural enterprises in China is low in general. Comprehensive technical efficiency (TE), pure technical efficiency (PE), and scale efficiency (SE) show a significant downward trend during 2013-2016. Financing efficiency decreased from a relatively high base of 0.754 in 2013 to 0.661 in 2016. And due to the increase in pure technical efficiency, the financing efficiency raised from 0.661 in 2016 to 0.730 in 2017. In the period between 2013 and 2017, the number of financing efficient enterprises is 11, 8, 7, 5, and 6, respectively. The proportion of financing efficient enterprises is 28.21%, 20.51%, 17.95%, 12.82%, and 15.38%, respectively, suggesting that more than 70% of agricultural enterprises are at a very low level of financing efficiency. From the distribution of the financing efficiency, both scale efficiency and pure technical efficiency are less than 0.9, which are the main reasons for the low financing efficiency.

4.3. Measurement of Total Factor Productivity Based on Malmquist Index. We analyze the financing efficiency of agricultural enterprises with Malmquist index model. The results shown in Table 4 indicate that the Malmquist indices of the first three periods were 0.984, 0.998, and 0.824, respectively, and exhibit a downward trend. And due to the increase in pure technical efficiency, the Malmquist

Table 2: Descriptive statistics.

Variables		Cases	Mean	S.D.	Max	Min
Financing efficiency evaluation variables	X_1	195	3.84	3.73	24	0.288
	X_2	195	1.58	1.97	11.1	0.044
	X_3	195	1.052	1.049	8.782	0.052
	Y_1	195	0.562	0.348	1.924	0.083
	Y_2	195	0.150	0.564	2.25	-2.197
	Y_3	195	2.273	18.293	62.715	-101.659
Influencing factors indicators	TL	195	1.774	2.07	16.416	0.015
	FE	195	0.051	0.084	0.788	-0.034
	RT	195	3.358	8.095	31.408	-43.175
	ITR	195	2.979	2.580	12.887	0.042
	PI	195	673.99	2.660	677.791	670.1
	GDP	195	6.962	0.792	8.207	5.930

Table 3: Financing efficiency values of agricultural enterprises.

	2013	2014	2015	2016	2017
Comprehensive technical efficiency (TE)	0.754	0.755	0.731	0.661	0.730
Pure technical efficiency (PE)	0.826	0.863	0.869	0.744	0.880
Sale efficiency (SE)	0.896	0.862	0.830	0.881	0.823

Table 4: Malmquist index of agricultural listed companies' financing.

Time	TC	EC	PTEC	SEC	TFP
2013-2014	1.013	0.971	1.054	0.961	0.984
2014-2015	0.969	1.03	1.008	0.962	0.998
2015-2016	0.897	0.919	0.846	1.06	0.824
2016-2017	1.12	1.279	1.199	0.934	1.433
mean	0.996	1.041	1.019	0.978	1.038

Table 5: Results of Tobit regression analysis.

Variables	Coefficient	Standard error	T-statistic	Prob
TL	-0.152	0.025	-6.14	0.001
FE	-0.057	0.025	-2.25	0.025
RT	0.012	0.002	5.97	0.001
ITR	0.011	0.005	1.94	0.053
PI	0.005	0.003	1.76	0.080
GDP	-0.042	0.097	-0.43	0.669
β_0	2.279	1.746	1.31	0.193

index raised to 1.433 during 2016-2017, and the Total Factor Productivity (TFP) growth rate was 43.3%. In the period between 2013 and 2017, the average TFP of agricultural enterprises' financing was 1.038, which indicates that the TFP increased by an average annual rate of 3.8%. In terms of composition, the average annual growth rate of technical change, efficiency change, pure technical efficiency change, and scale efficiency change was -0.4%, 4.1%, 1.9%, and -2.2%, respectively. The results indicate that the financing efficiency of agricultural enterprises is promoted by efficiency change and pure technical efficiency change and hindered by scale efficiency change.

4.4. Influencing Factors Analysis Based on Tobit Regression. We examine the effect of influencing factors on the financing efficiency of agricultural enterprises using Stata 14 software. The results shown in Table 5 indicate that, in addition to GDP, the other five influencing factors pass the significance test, and the performance of Tobit regression was remarkably good.

Total liability has a significant negative impact on agricultural enterprises' financing efficiency. The indicator of total liability is used to reflect the liability scale of enterprises. A 1% increase in total asset leads to a 0.152% decrease in agricultural enterprises' financing efficiency. This result

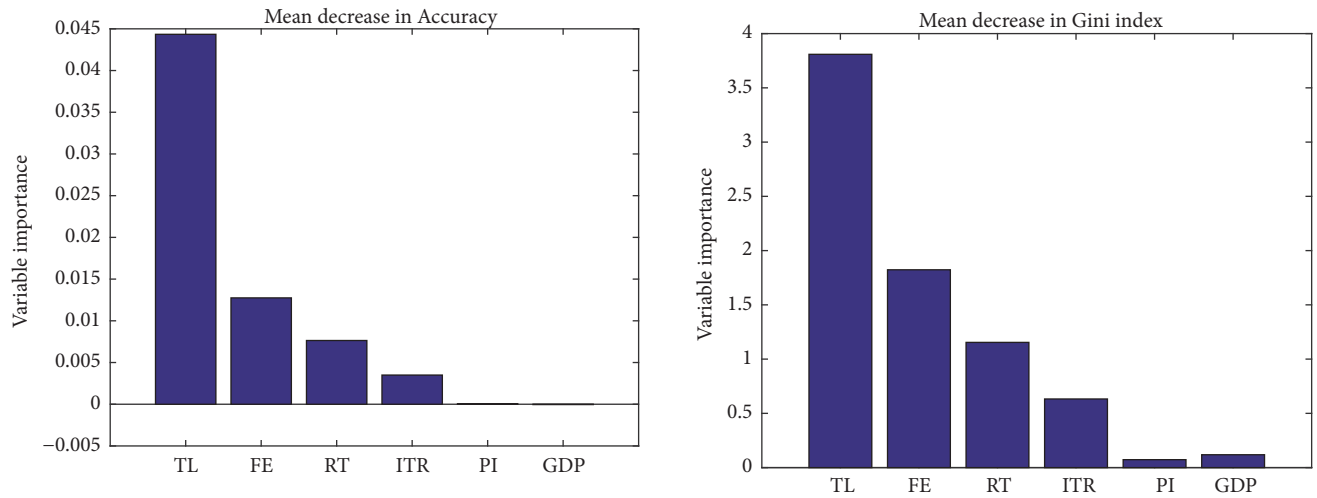

Figure 1: The importance ranking of influencing factors.

is consistent with the finding of Pan et al. for China's environmental protection industry [22]. The funds obtained by enterprises through debt need to be repaid, which will reduce the free capital of enterprises. Therefore, excessive debt financing will have a negative impact on the financing efficiency of agricultural enterprises.

Financial expense has a significant negative impact on agricultural enterprises' financing efficiency. A 1% increase in financial expense leads to a 0.057% decrease in agricultural enterprises' financing efficiency. This result is consistent with the finding of Gatti and Love (2010) and Wang and Zhang (2018), who found that higher financial costs lead to the lower financing efficiency of agricultural enterprises [23, 24].

Return on total assets is positively correlated with the financing efficiency of agricultural enterprises. A 1% increase in return on total assets leads to a 0.012% increase in financing efficiency. The result suggests that the stronger the enterprises' capital management ability is, the stronger the enterprises' profitability is, and the higher the financing efficiency of agricultural enterprises is, which confirms the findings of Wu and Zeng for SMEs (2019) [25].

Inventory turnover rate has a significant positive influence on the financing efficiency of agricultural enterprises. A 1% increase in asset-liability ratio leads to a 0.011% increase in financing efficiency. The result suggests that the higher the operating efficiency is, the higher the efficiency of enterprises financing is.

Price index of agricultural means of production has a significant negative impact on agricultural enterprises' financing efficiency. However, compared with other indicators, price index has little effect on the financing efficiency of agricultural enterprises. A 1% increase in price index of agricultural means of production only leads to a 0.005% increase in financing efficiency. This confirms the result of Pan et al. [22]. PI is a measure widely used to track agricultural production materials price inflation. Once inflation occurs, the rise of agricultural products prices will be a fatal blow to agricultural enterprises, which will inevitably affect the financing efficiency of enterprises.

GDP is negatively correlated with the financing efficiency, but it does not pass the significance test. The result suggests that GDP has no relation with the financing efficiency of agricultural enterprises.

On the whole, the negative impact of debt size and financing cost on financial efficiency is far greater than the positive impact of profitability and operating efficiency, while the impact of macroeconomic environment on the financing efficiency of agricultural enterprises is very limited.

4.5. Influencing Factors Analysis Based on Random Forest Regression. The impact of influencing factors on the financing efficiency of agricultural enterprises is also analyzed using random forest regression. Matlab package random forest developed by Abhishek Jaiantilal is used in this paper [46]. Firstly, we examine the importance ranking of influencing factors under the random forest approach. The results presented in Figure 1 indicate that the factors order of importance from strong to weak is total liability, financial expense, return on total assets, inventory turnover rate, price index of agricultural means of production, and GDP. Among them, external environmental factors, including price index of agricultural means of production and GDP, have little impact on financing efficiency of agricultural enterprises. This result is in agreement with that of Tobit regression.

Figure 2 presents the results of the impact of each factor on financing efficiency. It can be observed that the impact of total liability (TL), financial expense (FE), and GDP on financing efficiency is declining. When TL>4, FE>0.3, and GDP>7.15, the impact of these three factors in financing efficiency tends to be stable. The impact of return on total assets (RT) on financing efficiency is on the rise. When RT > 18, the impact of RT on financing efficiency tends to be stable. The impact of inventory turnover rate (ITR) on financing efficiency shows a downward trend from 0 to 4 and then an upward trend from 4 to 6. When ITR>6, the impact of ITR on financing efficiency tends to be stable. The influence of price

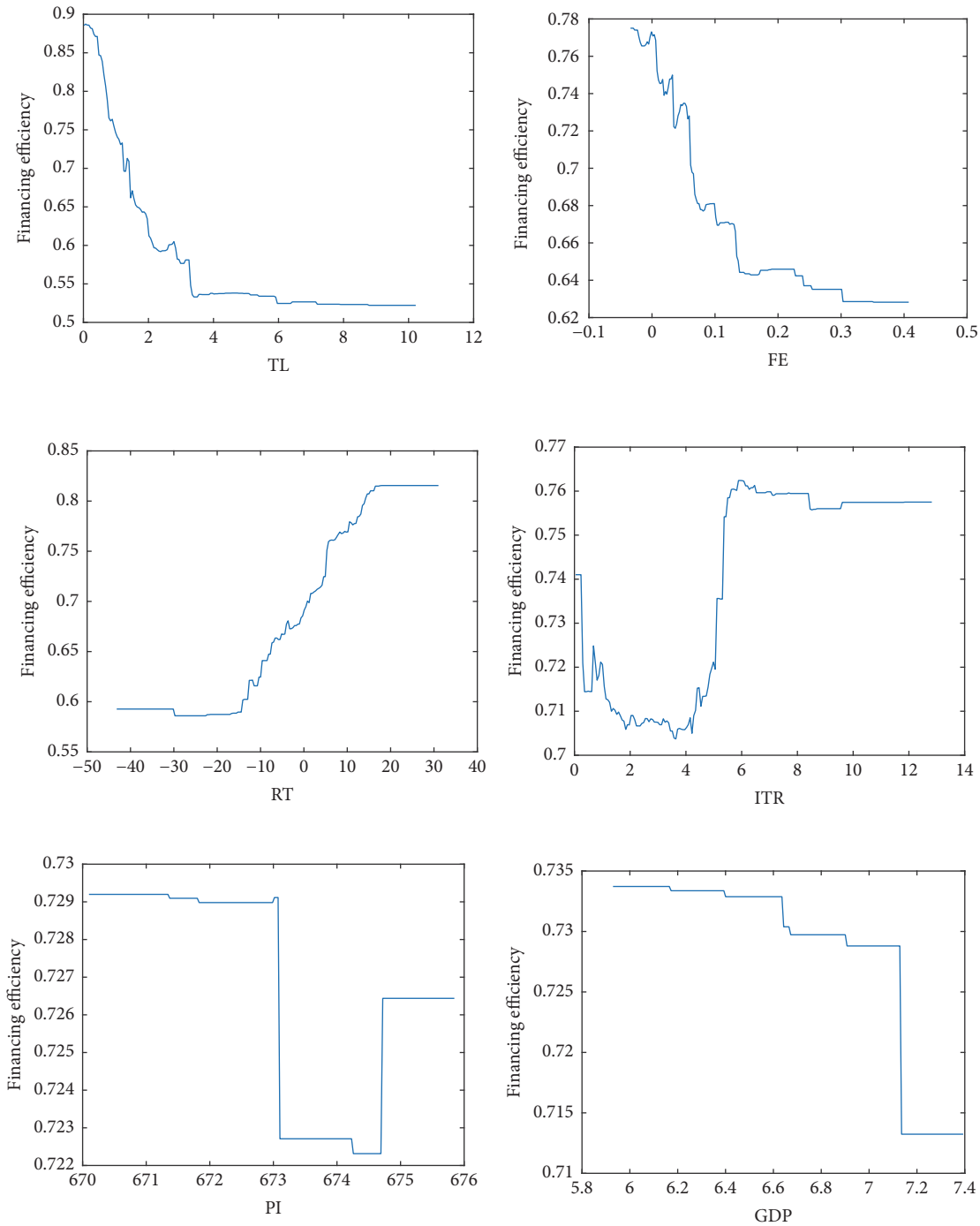

Figure 2: The impact of influencing factors on financing efficiency.

index of agricultural means of production (PI) on financing efficiency is U-shaped.

Taking the data of the first four years as training variables and the data of the last one year as testing variables, the empirical analysis is conducted with random forest regression model. Figure 3 shows that the R^2 value in training data and testing data is 0.946 and 0.748, respectively. We also compare the two regression methods. As shown in Figure 4, the R^2 value of the full data set based on random forest regression and Tobit regression is 0.913 and 0.577, respectively. The results suggest that, compared with Tobit regression, the analysis of financing efficiency based on random forest regression has higher R^2 values and better prediction results. Probably, the reason is the inability of the Tobit regression model in capturing the nonlinearity between financing efficiency of agricultural enterprises and its influencing factors.

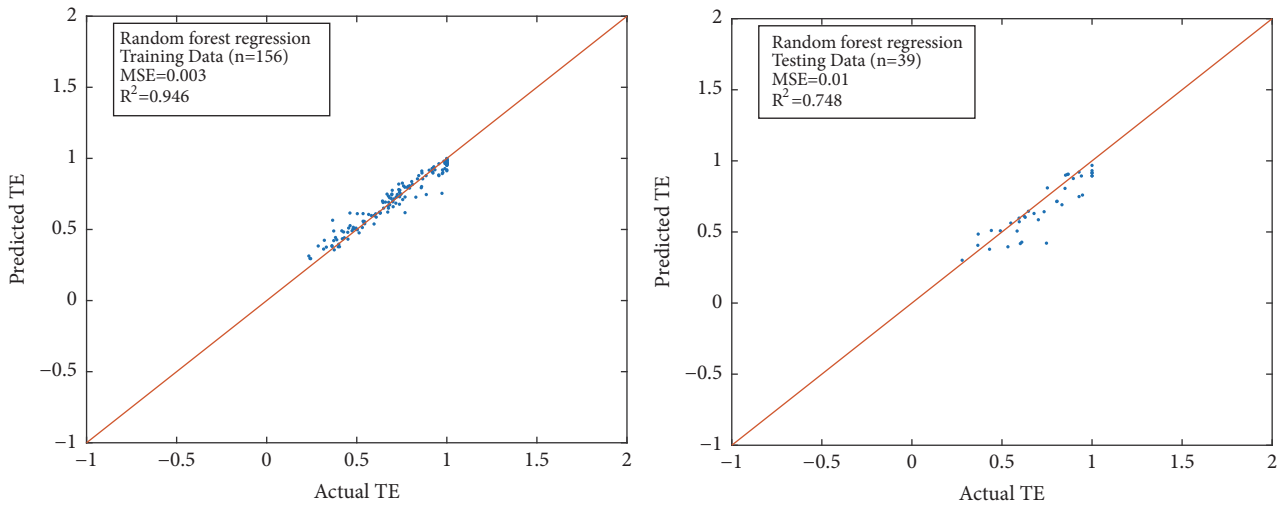

Figure 3: Predicted TE using random forest regression.

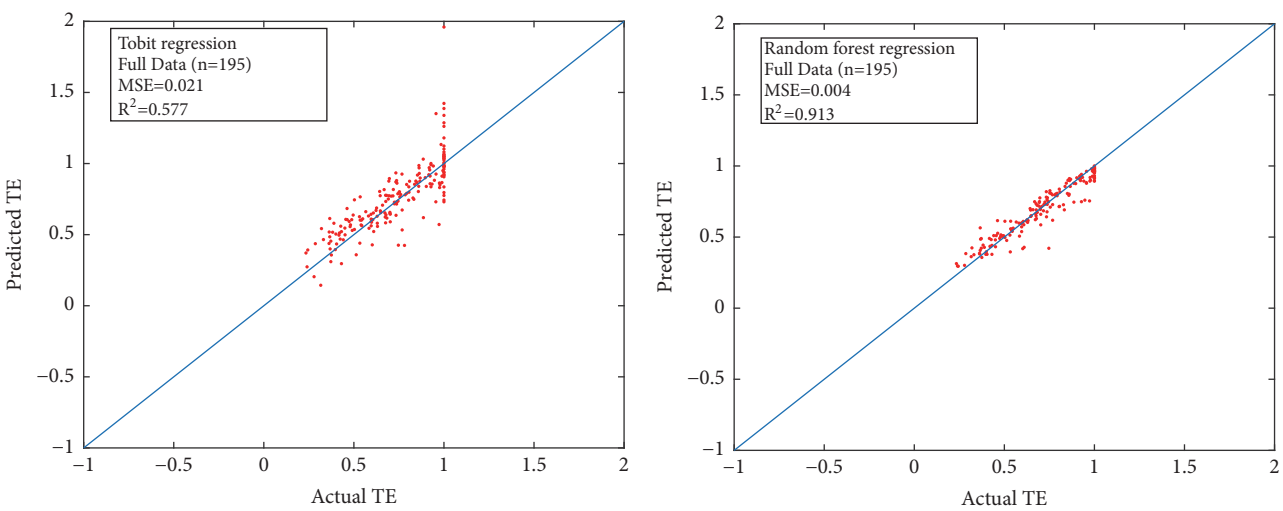

Figure 4: Comparison of predicted financing efficiency based on two regression models.

5. Conclusions and Recommendations

Using DEA model, this paper calculates financing efficiency of 39 agricultural listed companies in China from 2013 to 2017. The results reveal that the overall efficiency of financing of agricultural listed companies is low, and less than 30% of agricultural enterprises have achieved DEA effectiveness. Results of Malmquist index analysis indicate that, in the period of 2013-2017, the Total Factor Productivity (TFP) of agricultural enterprises has shown an upward trend due to the increase of efficiency change and pure technical efficiency change. Tobit regression and random forest regression have been applied to the analysis of influencing factors of financing efficiency of agricultural listed companies. The results indicate that random forest regression outperformed Tobit regression in terms of MSE and R^2. The improvement of return on total assets, inventory turnover rate, and the price index of agricultural means of production promote the increase of agricultural enterprises' financing efficiency. However, the significant increase in total liability and the expenditure of financial expenses is the main reasons for low financing efficiency of agricultural listed companies. In order to improve the financing efficiency of agricultural enterprises in China, the following suggestions are put forward.

(1) Improving the capital management ability of agricultural listed companies. Profitability is considered as a major factor for enhancing the enterprise's financing efficiency. Therefore, the enterprises should increase their project identification capabilities, invest their funds to agricultural projects with high returns, and strengthen their capital utilization efficiency. At the same time, the enterprises should establish an effective internal management system, effectively manage financial risks, and reduce unnecessary financial expenses.

(2) Expanding agricultural listed companies' financing channels and optimizing the financing structure.

Compared with other enterprises, agricultural enterprises are usually small in scale, weak in economic strength, vulnerable to the natural environment and social economy, and slow for the accumulation of funds. These characteristics result in relatively slow accumulation of internal funds and limited scale of external financing of agricultural enterprises. The enterprises should not be confined to bank loans, but take full advantage of various short-term and long-term financing resources such as microfinance, financial leasing, factoring, and bill discounting, and appropriately control the scale of debt financing of agricultural enterprises.

(3) Improving the government's ability to provide financing services for agricultural enterprises. The government should increase its support for the financing of agricultural listed companies and improve the policies for agricultural enterprise development from the aspects of market access, fair competition, and policy incentives. It ought to encourage innovation in financial products and businesses and build bridges between agricultural enterprises and financial institutions, so that the agricultural enterprises can find low cost funds. And the government also should strengthen regulation of listed companies, guard against illegal and irregular acts in the process of enterprises financing, protect the legitimate rights and interests of investors, and create a favorable financing environment for agricultural enterprises.

Data Availability

The data in this paper mainly come from the data of Listed Companies in China, which has been explained in Section 3.3 of the paper.

Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this paper.

Acknowledgments

This paper is supported by the Tianjin Planning Leading Group Office of Philosophy and Social Sciences under Grant Number TJYY17-017.

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