# Rural Financial Efficiency, Agricultural Technological Progress and Agricultural Carbon Emissions: Evidence from China

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## ABSTRACT

Based on the 30-province panel data in China during 2005-2018, this paper uses the DEA-SBM model and DEA-Malmquist model to measure rural financial efficiency and agricultural technological progress respectively and then uses the mediating effect model to analyze the linear influence. The results show that rural financial efficiency and agricultural technological progress both can inhibit agricultural carbon emissions, while agricultural technological progress plays a mediating role when rural financial efficiency influences agricultural carbon emissions. What's more, this paper uses the threshold effect model to analyze the non-linear influence. The findings reveal that when rural financial efficiency improves, the effects of rural financial efficiency and agricultural technology advances on agricultural carbon emissions shift from promoter to inhibitor.

## INTRODUCTION

Since the industrial revolution, mankind has over-exploited and over-utilized natural resources, and the global climate has become worse and worse. The greenhouse effect, which is produced by excess carbon dioxide emissions, has become a major source of worry among academics. Global warming might reach 1.5°C between 2030 and 2052 (IPCC 2018). The world is actively taking measures to combat global warming. At the 75th United Nations General Assembly in 2020, China stated that it will strive to peak carbon emissions by 2030 and achieve carbon neutrality by 2060. Various industries in China are actively exploring measures to reduce carbon emissions that are appropriate for them to meet these targets as soon as feasible.

Rapid agricultural development can ensure food security and economic benefits (Maraseni et al. 2020). However, as a largely agricultural country, China's share of global agricultural greenhouse gas emissions is constantly increasing, and in 2016 this share reached 13.07% (FAO 2020). Therefore, the current goal of China's agriculture isn't only to ensure food security, but also to protect the environment (Luo et al. 2014). Exploring the method of reducing agricultural carbon emissions is of great significance.

The Paris Agreement on Climate Change emphasized the important role of funding to address the challenges of climate change. Some academics have researched the influence of financial development on carbon emissions from a macroeconomic viewpoint in recent years. Shahbaz et al. (2018) stated that financial development can reduce carbon emissions. What's more, scholars have studied various influencing factors of agricultural carbon emissions, such as agricultural production (Owusu & Asumadu-Sarkodie 2016), rural population scale (Chen et al. 2018), agricultural economic development (Zhang & Liu 2018), energy consumption (Zhang et al.2019), urbanization (Ridzuan et al.2020), R&D investment (Chen & Li 2020) and industrial structure (Guo et al.2021). But there is little literature studying the influencing factor - rural finance. Therefore, the purpose of this paper is to investigate how rural financing influences agricultural carbon emissions.

Financial development helps to fund technical advancement, which in turn helps to minimize greenhouse gas emissions (Paroussos et al. 2020). Some researchers have looked at the mechanism of "financial development → technological progress → carbon emissions" from a macroeconomic perspective (Tamazian et al. 2009, Shahbaz et al. 2013, Yan et al. 2016). From the agricultural sector perspective, some scholars have only studied the relationship between the two, such as the impact of financial development on technological progress (Liu et al. 2021), and the impact of technological progress on carbon emissions (Chen & Li 2020). In general, only a few scholars have studied the mechanism of "rural financial development→agricultural technological progress→agricultural carbon emissions".

Based on the above background, this article, by using 30-province panel data in China during 2005-2018, studies the mechanism of "rural financial efficiency → agricultural technological progress→agricultural carbon emissions", and focuses on the following four analyses: (1) By measuring rural financial efficiency by DEA-SBM model, analyze the efficiency and quality of rural financial development, instead of only focusing on the financial scale and quantity. (2) By measuring agricultural technological progress by DEA-Malmquist model, analyze the dynamic changes of agricultural technological progress. (3) Using the mediating effect model, analyze the influence mechanism of rural financial efficiency on agricultural carbon emissions when agricultural technological progress plays the mediating role. (4) Using the threshold effect model, analyze the non-linear impact of rural financial efficiency and agricultural technological progress on agricultural carbon emissions.

This paper is structured as follows: Section 2 introduces past studies and hypothesis development. Section 3 introduces methodology. Section 4 presents results and discussion. Section 5 concludes.

**Past Studies and Hypothesis Development**

In the literature on the relationship between financial development and carbon emissions, scholars have different views. Some scholars believe that financial development can reduce carbon emissions. The main mechanisms are as follows: (1) A sound financial system can provide a good environment for carbon trading activities (Claessens & Feijen 2007). (2) Mature financial system can provide sufficient funds and comprehensive financial services for environmentally friendly projects (Tamazian & Rao 2010) and emission reduction projects (Zhou et al. 2019). (3) A sound financial system can provide support for low-carbon development through fiscal policy. For example, financial policy tools optimize the energy consumption structure of enterprises by adjusting energy prices (Zhou et al. 2019). However, some scholars believe that financial development can promote carbon emissions. According to Shen et al. (2021), a well-developed financial system aids corporations in expanding output and consumers in obtaining sufficient consumer credit, making it simpler to acquire high-energy-consuming commodities and thereby boosting carbon emissions.

There is little literature on the impact of rural finance on agricultural carbon emissions. This article will learn from the above mechanism, focus the research perspective on rural areas and the agricultural sector, and propose the following hypothesis:
**Hypothesis 1: Rural financial efficiency can inhibit agricultural carbon emissions:** In recent years, some

scholars have begun to study the impact mechanism of financial development on carbon emissions. Technological progress has been extensively studied as a mediating role of financial development influencing carbon emissions on the macro-level. The main mechanisms are as follows: (1) An open and free financial policy and a developed financial system can attract more R&D-related foreign direct investment, thereby promoting technological progress and then mitigating the country's environmental degradation (Tamazian et al. 2009) (2) A mature financial market has a strong and complete information disclosure system, which can reduce adverse selection and moral hazard caused by information asymmetry, and can enable the healthy development of technological innovation projects. Then technological progress will optimize the utilization of energy, thereby reducing carbon emissions (Shahbaz et al. 2013) (3) A well-developed finance market provides investors with a sound risk diversification mechanism. It can share the risk of return among different investors, thereby reducing investors' worries about investment in technology projects. Therefore, technology projects can proceed smoothly, and low-carbon technology projects will also receive strong support from the financial market to achieve emission reduction targets. (Zhou et al. 2019) (4) Financial development can improve the education system, thereby promoting the accumulation of human capital. Human capital carries out technological innovation, thereby promoting technological progress. Then technological progress will contribute to exploring new clean energy, thereby reducing carbon emissions (Zhou et al. 2019)

Some literature has studied the impact of rural finance on agricultural technology and the impact of agricultural technology on agricultural carbon emissions. Rural finance, according to Liu et al. (2021), may help agricultural technological innovation by easing the financial burden on creative businesses, diversifying investment risks in technology projects, and fostering talent for scientific research organizations. In particular, rural finance can provide financial support for farmers to use new technological tools, which can promote the application of agricultural technological innovation (Makate et al. 2019). Chen & Li (2020) stated that the advancement of agricultural technology will contribute to the low-carbon development of agriculture.

This article will learn from the above mechanism, focus the research perspective on rural areas and the agricultural sector, and establish a research mechanism of "rural financial efficiency→agricultural technological progress→agricultural carbon emissions". Hypothesis 2 is as follows:
**Hypothesis 2:** Agricultural technological progress plays a mediating role when rural financial efficiency influences agricultural carbon emissions

## MATERIALS AND METHODS

### Modeling

To verify hypothesis 1, the econometric equation (1) is set as:

$$ACEI_{it} = \alpha_0 + \alpha_1 fin_{it} + \alpha_2 gov_{it} + \alpha_3 stru_{it} + \alpha_4 env_{it} + \varepsilon_{it}$$
...(1)

To verify hypothesis 2, referring to the research of mediating effect of Wen and Ye (2014), equations (2) (3) are set as

$$tech_{it} = \beta_0 + \beta_1 fin_{it} + \beta_2 gov_{it} + \beta_3 stru_{it} + \beta_4 env_{it} + \varepsilon_{it}$$
...(2)

$$ACEI_{it} = \gamma_0 + \gamma_1 fin_{it} + \gamma_2 tech_{it} + \gamma_3 gov_{it} + \gamma_4 stru_{it}$$
$$+ \gamma_5 env_{it} + \varepsilon_{it}$$
...(3)

To analyze the non-linear impacts on agricultural carbon emissions, referring to the research of threshold effect of Hansen (1999), equations (4) (5) are set as:

$$ACEI_{it} = \theta_0 + \theta_1 fin_{it} \cdot I(fin_{it} \leq \eta_1) + \theta_2 fin_{it} \cdot$$
$$\cdot I(fin_{it} > \eta_1) + \theta X_{it} + \varepsilon_{it}$$
...(4)

$$ACEI_{it} = \sigma_0 + \sigma_1 tech_{it} \cdot I(fin_{it} \leq \rho_1) + \sigma_2 tech_{it} \cdot$$
$$\cdot I(fin_{it} > \rho_1) + \sigma X_{it} + \varepsilon_{it}$$
...(5)

Equations (1)-(5), $i$ represents the area. $t$ represents time. $\varepsilon_{it}$ is a random interference term. $\varepsilon_0$, $\beta_0$, $\gamma_0$, $\theta_0$ and $\sigma_0$ all represent constant terms. In equations (1)-(3), $\alpha_1$ and $\gamma_1$ represent the linear influence of $fin$ on $ACEI$. $\beta_1$ represents the linear influence of $fin$ on $tech$. The meanings of the rest of the coefficients can be deduced by analogy. In equations (4)-(5), $X_{it}$ represent the control variable. $\eta_1$ and $\rho_1$ are the threshold values. $I(\bullet)$ is the index function. When $fin$ meets the conditions in ( ), the value of the index function is 1, otherwise, it's 0. When $fin$ is less than or equal to the threshold value, the coefficient is $\theta_1$ or $\sigma_1$. When $fin$ is greater than the threshold value, the coefficient is $\theta_2$ or $\sigma_2$. Equations (4) and (5) are situations where there is a single threshold. If there are more thresholds, equations can be extended.

### Variables

**Dependent variable: *Agricultural carbon emission intensity* (*ACEI*):** Because agricultural carbon emissions are mostly caused by the use of agricultural resources (Hu et al. 2020), this article focuses on six key carbon sources. Table 1 shows the complete details. And the quantity of agricultural fertilizers, pesticides, agricultural diesel, agricultural plastic films, total planted area of crops, and effective irrigation area are all measured separately. The calculation formula for total agricultural carbon emissions is as follows:

$$ACE = \sum ACE_i = \sum \omega_i \bullet \mu_i$$
...(6)

$ACE$ is the total agricultural carbon emissions. $ACE_i$ is the carbon emissions of each carbon source. $\omega_i$ is the amount of each carbon source. $\mu_i$ is the carbon emissions coefficient of each carbon source.

Since agricultural carbon emission intensity (*ACEI*) is of greater practical meaning, this paper uses it to represent agricultural carbon emissions. And it's measured by the ratio of the total agricultural carbon emissions (*ACE*) to the total agricultural output value.

**Independent variable and threshold variable: *Rural financial efficiency* (*fin*):** This paper uses the DEA-SBM model proposed by Tone (2003) to measure China's rural financial efficiency. This model is a non-radial variable returns to scale DEA model that avoids mistakes due to radial direction assumptions while disregarding slack variables. The model is as follows:

$$
\begin{cases}
\min \alpha = \dfrac{1 - \dfrac{1}{a}\sum\limits_{p=1}^{a}\dfrac{S_p^-}{m_{p0}}}{1 + \dfrac{1}{b}\sum\limits_{q=1}^{b}\dfrac{S_q^+}{n_{q0}}} \\
m_0 = Mv + s^- \\
n_0 = Nv - s^+ \\
\sum v = 1 \\
v \geq 0, s^- \geq 0, s^+ \geq 0
\end{cases}
$$
...(7)

Table 1: The agricultural carbon source coefficients and references.

| Source | Coefficient | Reference |
|---|---|---|
| Fertilizers | 0.8956kg CE.kg$^{-1}$ | Oak Ridge National Laboratory |
| Pesticides | 4.9341kg CE.kg$^{-1}$ | Oak Ridge National Laboratory |
| Diesel fuel | 0.5927kg CE.kg$^{-1}$ | IPCC |
| Agricultural film | 5.1800kg CE.kg$^{-1}$ | Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University |
| Plowing | 312.6000kg CE.km$^{-2}$ | College of Biology and Technology, China Agricultural University |
| Irrigation | 20.4760kg CE.hm$^{-2}$ | Dubey and Lal (2009) |

The number of DMUs is W. The number of input variables is $a$. The number of output variables is $b$. $\nu$ is the weight vector. M represents the input index. N represents the output index. $\alpha$ is the efficiency value of DMU($m_0, n_0$). $S_p^-$ is the input slack variable. $S_q^-$ is the output slack variable. $\alpha \in [0,1]$. If and only if $S^- = S^+ = 0$, $\alpha=1$ and DMU is valid.

Based on the research of Atici et al. (2018), considering the rationality and availability of data, the following evaluation index system (shown in Table 2) is constructed:

**Mediating variable: *Agricultural technological progress* (*tech*):** In this paper, the DEA-Malmquist model proposed by Fare et al. (1994) is used to measure the agricultural technological progress in China. The advantage of this model is that it can reflect the dynamic changes of agricultural technological progress and the method isn't restricted by the function form or distribution assumptions. The corresponding frontier function can be obtained just by the method of linear programming, and the technological progress index can be calculated.

First, the DEA-BBC model is as follows:

$$
\begin{cases}
\min \beta = \theta - \varepsilon \left( \sum_{p=1}^{a} s_p^- + \sum_{q=1}^{b} s_q^+ \right) \\
\theta m_0 = Xv + s^- \\
n_0 = Yv - s^+ \\
\sum v = 1 \\
v \geq 0, s^- \geq 0, s^+ \geq 0
\end{cases}
$$
...(8)

The number of DMUs is W. The number of input variables is $a$. The number of output variables is $b$. $\theta$ is the target planning value. $\nu$ is the planning decision variable. $\varepsilon$ is non-Archimedes infinitesimal. X represents the input

index, and Y represents the output index. $\beta$ is the efficiency value of DMU ($m_0$, $n_0$). $S_p^-$ is the input slack variable, and $S_q^-$ is the output slack variable. If $\theta=1$, $S^- = S^+ = 0$, DMU is valid. If $\theta<1$, DMU is invalid. If $\theta=1$, and $S^- \neq 0$ or $S^+ \neq 0$, DMU is weak valid.

Second, the Malmquist index model is as follows:

$$
M\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[ \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}}
$$
...(9)

$$
Effch = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}
$$
...(10)

$$
Tech = \left[ \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}}
$$
...(11)

$$
Tfpch = Effch \times Tech = (Pech \times Sech) \times Tech
$$
...(12)

($x^t, y^t$) and ($x^{t+1}, y^{t+1}$) represent the input-output vector in period t and t+1 respectively. If index M>1, it means the efficiency increased. If index M<1, it means the efficiency declined.

Based on the research of Wang & Tan (2021), considering the rationality and availability of data, the following evaluation index system (as shown in Table 3) is constructed:

**Other Control Variables**

**Fiscal policy of supporting agriculture (gov):** It refers to the fiscal expenditure provided by the government to support local agricultural development. This article uses the ratio of fiscal expenditures of supporting agriculture to the total output value of agriculture to measure gov, which can reflect the extent of government support for local agricultural development.

**Farmland planting structure (stru):** It can be measured by the proportion of the sown area of food crops to the total sown area of crops. Different planting structures will have different impacts on agricultural carbon emissions. Compared with non-food crops, food crops require less agricultural

Table 2: Evaluation index system of rural financial efficiency.

| Evaluation subject | Index type | Index |
|---|---|---|
| Rural financial efficiency | Input | Total assets of rural financial institutions |
| | | Number of rural financial institution outlets |
| | | Number of employees in rural financial institutions |
| | | Agricultural loan balance of financial institutions |
| | Output | Added-value of agriculture |

Table 3: Evaluation index system of agricultural technological progress.

| Evaluation subject | Index type | Index |
|---|---|---|
| Agricultural technological progress | Input | Number of employees in agriculture |
| | | Total sown area of crops |
| | | Fixed asset investment in agriculture |
| | | Total power of agricultural machinery |
| | Output | Gross output value of agriculture |

film, fertilizers, pesticides, and other agricultural chemicals. Therefore, the larger the proportion is, the lower agricultural carbon emissions will be.

**Deterioration of rural environment (env):** It can be measured by the proportion of the affected area of crops to the total sown area of crops. Deterioration of the rural environment will lead to more natural disasters in rural areas. The more severe the damage to crops is, the greater the energy consumption and the increase in agricultural carbon emissions will be.

### Data Sources

Because the data of Tibet, Hong Kong, Macao, and Taiwan is incomplete, this paper uses 30-province panel data in China during 2005-2018 to empirically analyze the impact of *fin* and *tech* on *ACEI*. The main sources of the above data are the open data of the National Bureau of Statistics, Wind database, China Regional Financial Operation Report, China Financial Yearbook, China Rural Statistical Yearbook, China Agricultural Machinery Industry Yearbook, and China Statistical Yearbook. Parts of missing values are filled by interpolation. This article adjusts the magnitude of *ACEI* and *gov* so that the value of all variables is between 0-10. The detailed information of variables is shown in Table 4.

## RESULTS AND DISCUSSION

### Total Effect Analysis

This article uses a 14-year and 30-province short panel, so unit root testing isn't required. The results of the F-test and Hausman-test show that the fixed effects model is better than the OLS model and the random effects model. Table 5 lists the results of the OLS model (model 1), random effects model (model 2), and fixed effects model (model 3).

In model 3, the coefficient of the independent variable - *fin* is -1.0815, which is significant at 1%, indicating that *fin* can inhibit *ACEI*. Therefore, the validity of hypothesis 1 is proved. High-efficiency rural finance supports low-carbon agricultural development by capital turnover, risk-taking, etc. The analysis of the control variables is as follows: the

Table 4: Descriptive statistics of variables.

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| ACEI | 420 | 2.3163 | 0.8444 | 0.5451 | 5.1907 |
| fin | 420 | 0.5234 | 0.2809 | 0.0543 | 1.1232 |
| tech | 420 | 1.5956 | 0.7537 | 0.1864 | 6.2962 |
| gov | 420 | 0.1839 | 0.2168 | 0.0194 | 1.9408 |
| stru | 420 | 0.6624 | 0.1336 | 0.3628 | 0.9687 |
| env | 420 | 0.2111 | 0.1479 | 0.0000 | 0.9357 |

coefficient of *gov* is significantly negative at 1%, which reflects the great inclination extent of government policy toward green agriculture. The coefficient of *stru* is significantly negative at 1%. This is because food crops have lower demand for agricultural chemicals, resulting in lower carbon emissions. The coefficient of *env* is significantly positive at 1%, indicating that the higher the extent of rural environmental degradation is, the harder the low-carbon production of agriculture is achieved.

### Mediating Effect Analysis

Wen & Ye (2014) found that when the test results are significant, the sequential test is better than the Sobel test. And the Bootstrap test is better than the Sobel test. Therefore, the appropriate mediating effect test procedure is shown in Fig. 1. First, the coefficient $\alpha_1$ of the independent variable - *fin* in model 3 is -1.0815, and it's significant at 1%, so the argument of mediating effect can be grounded. Second, the coefficient $\beta_1$ of *fin* in model 4 is 0.7900, which is significant at 1%. And the coefficient $\gamma_2$ of the mediating variable - *tech* in model 5 is -0.5978, which is significant at 1%. Therefore, there is a significant indirect effect. Third, the coefficient $\gamma_1$ of *fin* in model 5 is -0.6092, which is significant at 1%, so there is also a significant direct effect. Fourth, compare the sign of $\beta_1 \gamma_2$ and $\gamma_1$. If their signs are the same, there is a partial mediating effect. The ratio of the mediating effect to the total effect is 43.67% ($\beta_1 \gamma_2 / \alpha_1$). Therefore, the validity of hypothesis 2 is proved.

### Robustness Test

This article uses three methods to test the robustness of the regression results:

(1) The samples from 2005 and 2018 are excluded. In Table 6, models 6 and 7 illustrate the findings. A mediating impact still exists, accounting for 42.28 percent of the total.

(2) Replace the mediating variable. Agricultural technological progress is measured by agricultural mechanization (*tech'*) instead, which is the ratio of the total power of agricultural machinery to the total sown area of crops. The results are shown in models 8 and 9 in Table 6. There is still a mediating effect, accounting for 33.65%.

(3) Insert the dependent variable's one-period lagged term into the model. The two-step SYS-GMM can effectively solve the dynamic panel's endogenous issue. The results are shown in models 10-12 in Table 6. In model 10, *fin* still inhibits *ACEI*. In model 11, *fin* still promotes *tech*. In model 12, *fin* and *tech* both still inhibit *ACEI*. The mediating effect is still significant. Therefore, the regression results are robust.

Table 5: Results of total effect test and mediating effect test.

| Variable | Model 1 OLS | Model 2 RE | Model 3 FE | Model 4 FE | Model 5 FE |
|---|---|---|---|---|---|
| | ACEI | ACEI | ACEI | tech | ACEI |
| fin | -0.8280*** (-5.96) | -1.0482*** (-5.50) | -1.0815*** (-4.60) | 0.7900*** (3.93) | -0.6092*** (-2.95) |
| tech | | | | | -0.5978*** (-11.67) |
| gov | -1.5388*** (-8.37) | -1.8929*** (-9.41) | -2.0265*** (-9.58) | 0.7513*** (4.15) | -1.5773*** (-8.48) |
| stru | 0.2004 (0.76) | -0.7884* (-1.66) | -3.6829*** (-4.11) | -1.1232 (-1.46) | -4.3544*** (-5.63) |
| env | 2.1204*** (9.06) | 2.4680*** (10.50) | 2.5915*** (10.82) | -1.4809*** (-7.23) | 1.7061*** (7.77) |
| cons | 2.4523*** (10.90) | 3.2143*** (8.93) | 5.1476*** (8.44) | 2.1007*** (4.03) | 6.4035*** (11.95) |
| N | 420 | 420 | 420 | 420 | 420 |
| $R^2$ | 0.3275 | 0.4151 | 0.4302 | 0.2182 | 0.5791 |
| F | 52.01*** | | 72.85*** | 26.94*** | 105.95*** |
| Wald Chi$^2$ | | 267.37*** | | | |
| Hausman | | Chi$^2$ = 20.92  P = 0.0003 | | Mediating Effect/Total Effect = 43.67% | |

Note: The t/z statistics are in parentheses, and the 10%, 5%, and 1% significance levels are represented by *, ** and ***, respectively.

Table 6: Robustness test results.

| Variable | Model 6 FE | Model 7 FE | Model 8 FE | Model 9 FE | Model 10 SYS-GMM | Model 11 SYS-GMM | Model 12 SYS-GMM |
|---|---|---|---|---|---|---|---|
| | tech | ACEI | tech' | ACEI | ACEI | tech | ACEI |
| fin | 0.7577*** (3.49) | -0.5029** (-2.30) | 0.1225*** (3.34) | -0.7175*** (-3.39) | -0.3990*** (-9.16) | 0.3956*** (12.91) | -0.1655*** (-2.63) |
| tech | | -0.6035*** (-11.03) | | | | | -0.0450** (-2.28) |
| tech' | | | | -2.9709*** (-10.25) | | | |
| controls | yes | yes | yes | yes | yes | yes | yes |
| ACEI(-1) | | | | | 0.8713*** (104.18) | | 0.8578*** (44.79) |
| tech(-1) | | | | | | 0.9760*** (97.68) | |
| cons | 2.4114*** (4.05) | 5.5679*** (9.23) | 0.7572*** (7.97) | 7.3973*** (12.66) | 0.1095 (0.36) | 0.5041 (1.63) | 0.0910 (0.17) |
| N | 360 | 360 | 420 | 420 | 360 | 360 | 360 |
| $R^2$ | 0.1907 | 0.5664 | 0.1791 | 0.5523 | | | |
| F | 19.20*** | 84.91*** | 21.06*** | 94.98*** | | | |
| AR(1)-P | | | | | 0.0002 | 0.0235 | 0.0002 |
| AR(2)-P | | | | | 0.1053 | 0.7406 | 0.1261 |
| Sargan-P | | | | | 0.9737 | 0.9969 | 1.0000 |
| | Mediating Effect/Total Effect =42.28% | | Mediating Effect/Total Effect =33.65% | | | | |
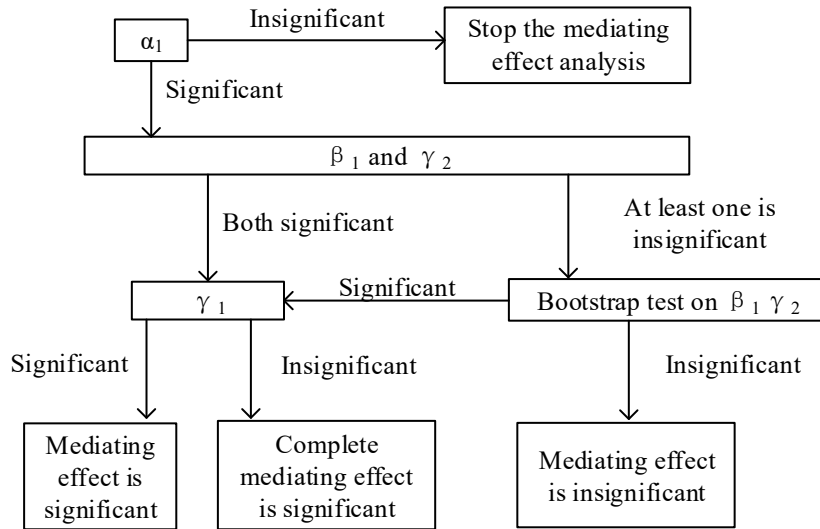
Fig.1: The mediating effect test procedure.

## Further Analysis: Threshold Effect Test

This paper selects *fin* as the threshold variable and selects *fin* and *tech* as threshold-dependent variables. To calculate the threshold values more precisely, the self-sampling approach (Bootstrap) is used 300 times. The results of the threshold effect test are shown in Table 7. When the threshold-dependent variable is *fin*, the single threshold test is significant at 1%, and the double threshold and triple threshold tests are not significant, so there is a single threshold with a threshold value of 0.0776, as shown in Fig. 2. When the threshold-dependent variable is *tech*, the double threshold test is significant at 5%, and the single threshold and triple threshold tests are not significant, so there is a double threshold with threshold values of 0.0776 and 0.4480, as shown in Fig. 3.

Then, regression estimation of the threshold effect model is performed, and the results are shown in Table 8. In model

13, when *fin*≤0.0776, the coefficient of *fin* is 17.0382, which is significant at 1%, indicating that when *fin* doesn't cross the single threshold, it's at a low level and it promotes *ACEI*. The reason may be that, at this time, its effect on the expansion of the agricultural production scale is greater than its effect on technology improvement. When *fin*>0.0776, the coefficient of *fin* is -1.1360, which is significant at 1%, indicating that when *fin* crosses the single threshold, it's at a relatively high level and it has an inhibitory effect on *ACEI*. The reason may be that, at this time, its effect on technology improvement is greater than its effect on the expansion of the agricultural production scale. In model 14, when *fin* ≤0.0776, the coefficient of *tech* is 0.6250, which is significant at 1%, indicating that when *fin* is too low, *tech* has a positive impact on *ACEI*. The reason may be that, at this time, rural finance cannot provide sufficient support for agricultural technological innovation. When 0.0776<*fin*≤0.4480, the coefficient of *tech* is -0.3946,

Table 7: Results of the significance test of the threshold effect.

| Threshold-dependent variable | Item | F-statistics | P-value | Threshold Estimation value | 95% confidence interval | 10% Critical value | 5% Critical value | 1% Critical value |
|---|---|---|---|---|---|---|---|---|
| Fin | Th-1 | 33.39*** | 0.0033 | 0.0776 | [ 0.0752 , 0.0851 ] | 18.5435 | 24.2863 | 29.0024 |
|  | Th-21 | 14.24 | 0.3267 | 0.0776 | [ 0.0752 , 0.0851 ] | 88.2282 | 100.8478 | 115.5176 |
|  | Th-22 |  |  | 0.5337 | [ 0.5233, 0.5424 ] |  |  |  |
|  | Th-3 | 9.23 | 0.7300 | 0.8995 | [ 0.8330 , 0.9439 ] | 55.3573 | 73.0685 | 116.7123 |
| tech | Th-1 | 35.33 | 0.1033 | 0.4480 | [ 0.4360 , 0.4587 ] | 35.3562 | 41.5207 | 54.1176 |
|  | Th-21 | 42.31** | 0.0133 | 0.4480 | [ 0.4272 , 0.4587 ] | 24.4556 | 29.4876 | 43.9099 |
|  | Th-22 |  |  | 0.0776 | [ 0.0752 , 0.0851 ] |  |  |  |
|  | Th-3 | 29.40 | 0.6533 | 0.1876 | [ 0.1818 , 0.2061 ] | 115.9801 | 126.1179 | 146.6378 |

Table 8: Regression results of the threshold effect.

| Variable | Model 13 | Model 14 |
|---|---|---|
| fin(fin≤0.0776) | 17.0382*** (5.28) | |
| fin(0.0776<fin ) | -1.1360*** (-5.01) | |
| tech （fin≤0.0776） | | 0.6250*** (3.53) |
| tech(0.0776<fin≤0.4480) | | -0.3946*** (-7.03) |
| tech （0.4480<fin） | | -0.7409*** (-14.35) |
| controls | yes | yes |
| cons | 4.6868*** (7.91) | 5.6276*** (11.23) |
| N | 420 | 420 |
| $R^2$ | 0.4735 | 0.6416 |
| F | 69.24*** | 114.57*** |

which is significant at 1%, indicating that when *fin* crosses the first threshold, *tech* has an inhibitory effect on *ACEI*. When fin>0.4480, the coefficient of *tech* is -0.7409, which is significant at 1%, indicating that the higher rural financial efficiency is, the stronger the support for agricultural technological progress will be, resulting in the stronger inhibition on agricultural carbon emissions.

## CONCLUSIONS

This paper uses the DEA-SBM model and DEA-Malmquist model to measure rural financial efficiency and agricultural technological progress respectively from the perspective of
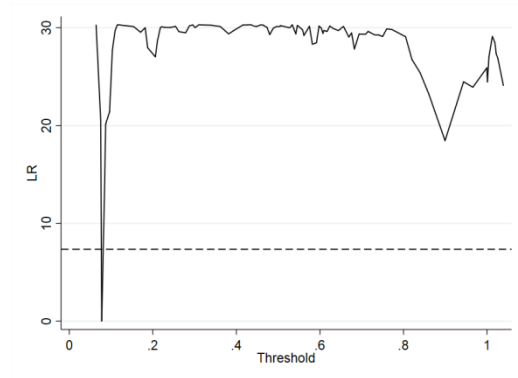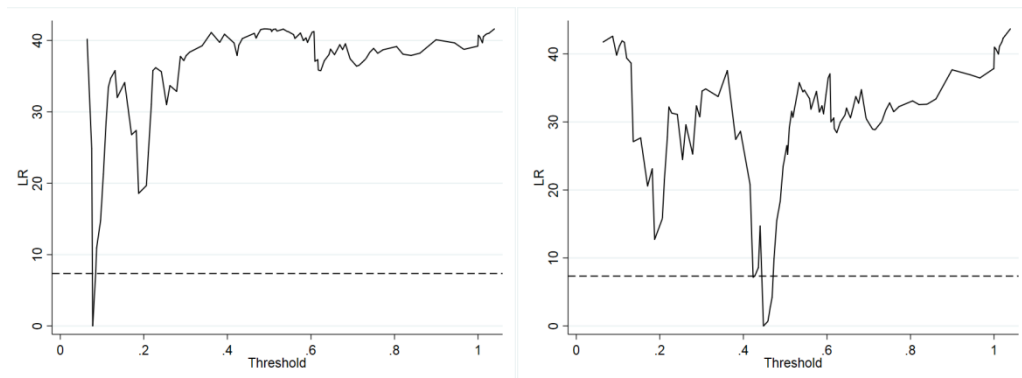


Fig. 2: Threshold estimated value and confidence interval (threshold-dependent variable: *fin*).

input and output. And it empirically studies the impact of rural financial efficiency and agricultural technological progress on agricultural carbon emissions by using provincial panel data from 2005-2018. The mediating effect model is used to demonstrate the mechanism of "rural financial efficiency-agricultural technological progress-agricultural carbon emissions". The panel threshold effect model is used to study the non-linear impact of rural financial efficiency and agricultural technological progress on agricultural carbon emissions. The main conclusions are as follows:

(1) Rural financial efficiency not only has a direct inhibitory effect on agricultural carbon emissions but can also inhibit agricultural carbon emissions by promoting agricultural technological progress.

(2) When rural financial efficiency is the threshold-dependent variable, it has a single threshold effect on agricultural carbon emissions. When rural financial efficiency



(a)                (b)

Fig. 3: The first (a) and second (b) threshold estimated values and confidence intervals (threshold-dependent variable: *tech*).

does not exceed the threshold, it promotes agricultural carbon emissions. And when rural financial efficiency crosses the threshold, it inhibits agricultural carbon emissions.

(3) When agricultural technological progress is the threshold-dependent variable, it has a double threshold effect on agricultural carbon emissions. When rural financial efficiency hasn't crossed the first threshold, agricultural technological progress promotes agricultural carbon emissions. When rural financial efficiency crosses the first threshold, agricultural technological progress inhibits agricultural carbon emissions. When rural financial efficiency crosses the second threshold, agricultural technological progress has a stronger inhibitory effect on agricultural carbon emissions.

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