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Agricultural carbon financial innovation and carbon emission reduction effect: an empirical study based on system GMM

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ABSTRACT
In recent years, the green economy has been developing rapidly, and the environmentalization of industries has been widely popularized in various industries. This paper carries out an in-depth study on the relationship between agricultural carbon finance and carbon emission reduction, and after understanding the theory related to carbon finance and carbon emission, it adopts the method of system GMM estimation to construct a dynamic panel model for the study of agricultural carbon finance and carbon emission, and selects research variables. The development of agricultural carbon financial innovation and carbon emission in 30 provincial-level administrative regions in China from 2014 to 2024 is studied, and regression analysis is carried out using system GMM so as to obtain the relationship between the impact of agricultural carbon financial innovation on carbon emission reduction, and the robustness test is carried out. The maximum values of agricultural carbon financial scale, carbon financial efficiency, carbon financial structure, and per capita carbon emission are 16.942, 7.052, 1.926, and 128.945 respectively, while the minimum values are 0.965, 0.048, 0.079, and 0.145 respectively, and the maximum values are 17.56, 146.92, 100.33, and 889.28 times of the minimum values. There are large differences in the development of agricultural carbon financial innovation and carbon emission reduction effects among different provinces. Per capita carbon emissions are reduced by 22.5%, 20.5% and 24.5% for each unit increase in carbon financial scale, carbon financial efficiency and carbon financial structure, respectively. The parameter estimates of carbon financial scale, carbon financial efficiency, and carbon financial structure are significant at the levels of 10%, 1%, and 5%, respectively. It indicates that the innovative development of agricultural carbon finance can effectively promote carbon emission reduction.
Keywords: system GMM estimation; regression analysis; carbon financial innovation; carbon emission reduction

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1. Introduction

Systematic GMM method is a method for estimating parameters of panel data models which combines instrumental variables of first-order difference and second-order difference. The GMM method is a special case of generalized moment estimation, which solves the problems of endogeneity and omitted variables by using instrumental variables [1-4]. Endogeneity and omitted variables are common problems in panel data models, and the systematic GMM method can effectively solve these problems and improve the accuracy and robustness of parameter estimation. It is of great significance in the research of agricultural carbon finance innovation and carbon emission reduction effect [5-8].

Carbon finance refers to a variety of financial institutional arrangements and financial trading activities aimed at reducing greenhouse gas emissions, including trading of carbon emission rights and derivatives, investment and financing of low-carbon project development, green credit of banks and other related financial intermediary activities [9-12]. As a kind of financial innovation, carbon finance has attracted more and more financial market participants to invest in the field of combating climate change and developing low carbon economy, in order to avoid the risks brought by climate change and obtain the opportunities brought by low carbon economy [13-16]. Agricultural carbon emissions are one of the major sources of global greenhouse gas emissions. Reducing agricultural carbon emissions is highly dependent on agricultural technological innovation, which requires a large amount of capital investment [17-18]. From the perspective of China's green financial system design, the realization of carbon emission reduction effect needs to be strengthened through the construction of perfect agricultural carbon emission accounting methods and low-carbon agricultural project evaluation standards, strengthening agricultural carbon subsidies and other ways to strengthen the policy guidance on agricultural carbon emission reduction, promote the innovative application of digital technology in the field of financial support for agricultural carbon emission reduction, and build an effective risk-sharing mechanism for agricultural carbon emission reduction [19-22].

At present, there is no direct point out in the academic field of "agricultural carbon finance innovation and carbon emission reduction effect", and there is no way to see the application of system GMM in this field, but there are many studies related to "agricultural financial innovation" and "carbon emission reduction effect", especially at the moment when carbon emissions continue to be serious, green finance plays an important role. Literature [23] adopted the green finance indicator system and applied the generalized method of moments and greenSolow model to conduct a multiple two-step analysis of the data on green technology innovation channels in China. It revealed that green finance development has a significant effect on reducing CO2 emissions. Literature [24] examined the impact of green finance on agricultural pollution and carbon emission reduction, and obtained the conclusion that "green finance has a significant impact on reducing both agricultural pollution and carbon emission". And put forward relevant suggestions to promote carbon emission reduction and pollution reduction. Literature [25] points out a series of environmental problems brought about by the development of agriculture, and discusses the extent to which the development of green finance in China effectively contributes to the reduction of carbon emissions from agriculture by using a two-way fixed effects model. It is illustrated that green finance is beneficial to the reduction of carbon emissions. Literature [26] introduced digital financial inclusion as an important way to achieve sustainable development. The fixed and mediating effects of agricultural carbon emissions were explored using fixed and mediating effects models. Positive conclusions such as "digital inclusive finance is conducive to reducing agricultural carbon emissions" were obtained. Literature [27] investigated the impact of green finance on fertilizer use and agricultural carbon emissions, using standardized test framework, variance decomposition analysis and other methods, revealing that green finance has an important supportive role in achieving carbon emission reduction targets. Literature [28] demonstrated the important role of reducing agricultural carbon emissions, explored the impact of policies on agricultural carbon emission reduction (ACER), obtained conclusions such as policies are favorable to reduce agricultural carbon emissions, and put forward suggestions to reduce carbon emissions. Literature [29] describes the role of the agricultural sector in achieving carbon emission reduction and green transition. It is pointed out that green production technology in agriculture plays an important role in reducing carbon emissions. And through the establishment of regional synergistic emission reduction mechanism, it is conducive to the realization of agricultural carbon emission reduction and green development. Literature [30] clarified that green finance effectively promotes agricultural carbon emission reduction. It also pointed out that the current distribution of this promotion is uneven, which requires policymakers to implement differentiated green finance implementation strategies, promote the structural adjustment of the agricultural industry, and encourage the introduction and use of innovative low-carbon technologies.

The study aims to clarify the impact of agricultural carbon financial innovation and development on carbon emissions, so it conducts in-depth research on theories related to carbon finance and carbon emissions, and puts forward preliminary hypotheses on this basis. The research model between the innovative development of agricultural carbon finance and carbon emission is constructed through the method of systematic GMM estimation, defining the explanatory variables, explanatory variables and control variables. After the descriptive statistics of the variables are conducted with 30 provinces in China as the research object, the unit root test is used to ensure the smoothness of the panel data. After regressing the dynamic panel model, the model is estimated by systematic GMM method to get the correlation between carbon emissions and the development of agricultural carbon finance innovation. Finally, the robustness test was conducted by 1% shrinking tail treatment and replacement metric method.

2. **Carbon financial innovation and carbon emission theory analysis**

2.1. The concept of carbon finance

After the official implementation of the Kyoto Protocol, the low-carbon economy began to develop, and the carbon trading market became a favorable tool for the development of the low-carbon economy. With the continuous improvement of the carbon trading market mechanism and the expansion of the scale of carbon trading, the investment and financing activities of the low-carbon economy supporting it began to develop, and carbon finance came into being. Carbon finance, also known as carbon financing and trading of carbon substances, refers to various financial trading activities and institutional arrangements for the purpose of reducing greenhouse gas emissions and realizing emission reduction targets, covering a variety of elements such as markets, products, services, institutions and policies, and mainly including direct investment and financing, carbon rights trading, bank loans and other financial activities that serve to limit greenhouse gas emissions and other technologies and projects.

Carbon finance is a resource for projects that generate or can generate greenhouse gas emission reductions by purchasing emission reductions [31]. Three characteristics of carbon finance: the establishment of a market for two new commodities, carbon allowances and carbon neutrality, investment and financing activities containing clean energy, and the assessment of carbon risks and rewards.

Carbon finance is divided into broad and narrow sense, the narrow sense of carbon finance refers to all investment and financing activities that serve greenhouse gas emissions, including the trading of carbon emission rights and their derivatives. Carbon finance in the broad sense includes not only financial activities related to carbon emission rights in the narrow sense, but also financial services to address climate change and low-carbon economic development. In addition carbon financial products are powerful tools to promote the development of the carbon financial market, which can be categorized into three major categories: trading tools, financing tools and support tools. Among them, carbon market trading tools refer to carbon spot products of carbon assets, mainly carbon futures, carbon forwards, carbon options and carbon swaps, as well as carbon asset securitization and indexed carbon trading products. Carbon market financing tools can create valuation and realization pathways for carbon assets, and help small and medium-sized emission reduction enterprises to solve the problem of financing difficulties, including carbon pledge, carbon repurchase and carbon trusteeship business.

Carbon support tools and related services, including carbon indices, carbon insurance and carbon funds, can provide windsocks for all parties to understand the trends of the carbon market, as well as risk management and market credit enhancement tools for the management of carbon assets. In order to realize the smooth development of carbon market transactions and related financial activities, banks and other financial institutions provide these related carbon financial products and services, and the government is responsible for the development of related carbon emission reduction mechanisms to promote the transformation of enterprises into a low-carbon economy. In this paper, carbon finance mainly refers to the carbon financing business related to financial institutions, carbon market trading and carbon tax and other governmental emission reduction tools.

2.2. Theories related to carbon emissions

1) Environmental Kuznets Curve Theory. Environmental Kuznets Curve (EKC) reflects the relationship between the level of economic development and environmental quality [32], roughly inverted U-shape, with the different degree of economic development, economic growth will change the degree of pollution of the environment. When the economic growth of backward areas to a certain extent, that is, to reach a certain “inflection point”, even if the residents' income increases, environmental pollution has gradually slowed down, environmental quality can also be improved.

2) Sustainable Development Theory. This theory refers to the fact that development should not only meet the needs of the current society, but also meet the survival and development needs of future generations, and adhere to the principles of continuity, fairness and commonality. Sustainability is ultimately about realizing multidimensional coordinated development. The theory of sustainable development not only covers social, ecological and economic aspects, but also guides the development of human society. To realize the coordinated and healthy development of the whole society, it is necessary to promote industrial sustainability, insist on industrial decarbonization, and apply it to all aspects of the social system.

3) Low-carbon economic theory. Low-carbon economic theory refers to the social development pattern that adheres to the concept of sustainable development, utilizes technological innovation, institutional innovation and the development of new energy sources to establish a low-carbon industrial system and a low-carbon energy system, reduces fossil energy consumption such as petroleum and coal as much as possible, and thus reduces greenhouse gas emissions and achieves a win-win situation between economic development and environmental protection. Low-carbon economy follows the principle of market development, promotes the common development of economy and ecology on the basis of meeting the basic needs of human beings, and stimulates the potential of energy saving and emission reduction in many fields, such as the living field, industrial field and consumption field. Nowadays, low carbon economy has become a strategic research and an important way to achieve efficient and coordinated economic development, environmental sustainability and industrial decarbonization in many countries in the world.

Based on the above analysis, this paper puts forward the following hypothesis: agricultural carbon financial innovation can carbon emission reduction has a positive impact.

3. Research design

3.1. System GMM Estimation

Panel data are developed from time-series data and cross-section-series data, and are a combination of the two, being repeated observations of individual cross-sectional units over time. Comparing panel data with time series data or cross sectional series data, the degrees of freedom are increased and the possible covariance problems between explanatory variables are reduced, thus making the estimation results more valid. Repeated observations for the same cross-sectional unit values provide a better study of the dynamics of changes in economic behavior. It takes the general form of:

$$y_n = \alpha + \beta X_i + \mu_i + e_n \tag{1}$$

where i represents a different sample $(i = 1, \ldots, N)$; t represents a different time of year $(t = 1, 2 \ldots, T)$, X_{it} contains k explanatory variables, μ_n is an unobserved cross-section individual effect, and $e_{i,s}$ represents a random error term.

Panel data has one of the more obvious advantages of modeling the dynamic behavior of a sample of individuals. Because of inertia or partial adjustment, an individual's current behavior may be influenced by past behavior, as is the case with capital stock adjustment. If the lagged term of an explanatory variable also becomes a member of the explanatory variables in a panel model, the model is called a "dynamic panel data model", i.e., a dynamic panel model is a model that adds the lagged term of the explanatory variable y to the right-hand side of (1), so that the lagged term of the dependent variable also becomes an explanatory variable. The basic form is:

$$y_t = \lambda y_{n-1} + \beta X_{in} + \mu_i + e_n \tag{2}$$

Dynamic panel data models have the outstanding advantage of controlling for fixed effects [33], better overcoming the problem of omitted variables, and also eliminating the problem of reverse causation. However, the fact that y_{it-1} is used as an explanatory variable makes the explanatory variable correlated with the disturbance term, which makes the dynamic panel model suffer from the problem of endogeneity; in addition, the model contains unobserved fixed or random effects, and the unobserved effects are related to the lagged term of the dependent variable, which makes most of the traditional estimation methods give inconsistent results, which in turn makes a certain distortion of the inferred economic meanings. To address this problem GMM estimation methods have emerged.

GMM is a first-order differencing of the level equations to eliminate the individual effects of the unobserved cross sections, and uses the prior term of the explanatory variables and the lagged term of the explanatory variables as instrumental variables to solve the endogeneity problem and the heteroskedasticity of the residuals. However, GMM estimation is mostly used in the case of a large number of cross-sections and a small number of time series, and GMM estimation has some drawbacks in that not only the individual effects of unobserved cross-sections are eliminated when differencing, but also other variables that do not change over time are eliminated as well. Moreover, due to the influence of weak instrumental variables GMM estimation yields non-effective estimates. On the basis of differential GMM, the moment condition is added to make the lag term of the dependent variable difference orthogonal to the random error term, and by combining the level equations and differential equations as a system of equations for GMM estimation, systematic GMM estimation emerges to solve these problems and improve the estimation effect. To summarize, so this paper adopts the system GMM method to estimate the model.

System GMM estimation is to perform first-order differencing [34] on the equations, use appropriate instrumental variables to generate moment-conditional equations to eliminate fixed effects, and then use the lagged terms of the explanatory variables as instrumental variables in the differencing equations to obtain consistent estimates. System GMM estimation does not require information about the distribution of the random error term, so the parameter estimates obtained by this method are more effective than other traditional parameter estimation methods. The system GMM is based on equation (2) with first order differencing to obtain equation (3):

$$\Delta y_{it} = \lambda \Delta y_{it-1} + \beta \Delta X_{it} + \Delta e_{it} \tag{3}$$

From equation (2), we know that y_{i-1} is a function of e_{n-1}, so $\Delta y_{n-1}\left(= y_{t-1} - y_{t-2}\right)$ and $\Delta e_{ij}\left(= e_{ij} - e_{ij-1}\right)$ in (3) are related. In estimating equation (3), instrumental variables for Δy_{it-1} need to be introduced. Take y_{it-2} and Δy_{i-2} as instrumental variables because they are correlated with Δy_{y-1} and uncorrelated with Δe_n.

Then the following moment conditions are applied:

$$f(\alpha) = \sum_{i=1}^{n} f(\alpha)_i = \sum_{i=1}^{n} z_i e_i(\alpha) \tag{4}$$

where $e_i(\alpha) = \Delta y_{it} - \alpha_1 \Delta y_{it-1} - \sum_{i=1}^{n} \alpha_i \Delta X_{kit-1}$, z_i are the instrumental variables taken.

The basic principle of GMM estimation is to minimize the following objective function

$$S(\alpha) = \left[\sum_{i=1}^{n} z_i' e_i(\alpha)\right]' H \left[\sum_{j=1}^{n} z_i' e_1(\alpha)\right] = f(\alpha)' H f(\alpha) \tag{5}$$

where H is the weight matrix and is positive definite.

Two main tests are used to verify the suitability of the system GMM estimation for use. The first one is the Sargan test, which focuses on testing the accuracy of the instrumental variables in the presence of overidentification, with the original hypothesis that the selected instrumental variables satisfy the moment condition (no overidentification). The second test is the Arellano Bond serial autocorrelation test, with the original hypothesis that there is no serial correlation. When the regression residual terms are independently and identically distributed, the first order differences of the residuals are autocorrelated, and if the order of autocorrelation exceeds one it means that the GMM may not be valid. The system GMM estimate is between the fixed effects estimate and the mixed least squares estimate because mixed least squares regression typically grossly overestimates the coefficient values of the lagged terms, while fixed effects models underestimate the coefficient estimates of the lagged terms, so if the estimate obtained by the system GMM is somewhere in between, then the system GMM estimate is a valid estimate.

3.2. Modeling

According to the existing research and the analysis in the previous chapters, in order to study the impact of carbon financial innovation and development on carbon emissions, this paper establishes the following basic analytical model:

$$CO_2 = f\left(fd, et, gdp, X\right) \tag{6}$$

Where CO_2 represents carbon emissions, fd represents carbon financial innovation and development indicators, gdp represents economic growth, and X is other control variables, which are added to make the model results more accurate.

Dynamic panel data models (7) and (8) are set up on the basis of the basic model (6) for systematic GMM estimation.

1) The role mechanism model of the impact of carbon financial innovation and development on carbon emissions:

$$\ln CO_{2i,t} = \alpha_i \ln CO_{2i,t-1} + \beta_{i1} \ln ET_{i,t} + \beta_{i2} \ln GDP_{i,t} + \gamma_i \ln FD_{i,t} + \lambda_i X_{it} + v_i + \varepsilon_{i,t} \tag{7}$$

2) Carbon finance innovation and development has a deteriorating and then improving effect on carbon emissions, i.e., an inverse U-type validation model:

$$\ln CO_{2i,t} = \alpha_i \ln CO_{2i,t-1} + \beta_{i1} \ln ET_{i,t} + \beta_{i2} \ln GDP_{i,t} + \gamma_i \ln FD_{i,t} + \delta\left(\ln FD_{it}\right)^2 + \lambda_i X_{it} + v_i + \varepsilon_{i,t} \tag{8}$$

where the meaning of each variable is unchanged and is the same as in (6). i represents different provinces, t represents different year times, v_i represents regional fixed effects, and $\varepsilon_{i,t}$ represents the random error term.

Model (7) is mainly used to test whether carbon financial innovation is conducive to the reduction of carbon emissions, and the squared term of carbon financial innovation-related indicators is added to model (8) to test whether there is an inverted U-shaped relationship between carbon financial innovation and carbon emissions, i.e., the increase in the level of carbon financial innovation firstly leads to the increase of carbon emissions, and then the carbon emissions will decrease with the improvement of the level of carbon financial innovation after reaching a certain value.

3.3. Definition of variables

The variables in this paper are defined as shown in Table 1.

Table 1. Variable definition and calculation method

Variable type	Variable symbol	Variable name
Explained variable	pc	Per capita carbon emissions
Interpretation variable	Acs	Agricultural carbon financial scale
	Ace	Agricultural carbon financial efficiency
	Acfs	Agricultural carbon financial structure
Control variable	pgdp	Economic growth
	Ind	Industry structure
	Tech	Technological progress
	FDI	Foreign direct investment
	Inv	Investment strength
	Human	Human capital level
	inf	Infrastructure level

4. Empirical findings

4.1. Descriptive statistics of variables

The research scope of this paper is 30 provincial-level administrative regions (except Hong Kong, Macao, Taiwan and Tibet), and 425 cities' agricultural carbon financial innovation and carbon emission reduction development are studied in depth. The descriptive statistics of each variable are shown in Table 2, which describes and analyzes the main variables. Among them, the maximum values of agricultural carbon financial scale (Acs), carbon financial efficiency (Ace), and carbon financial structure (Acfs) in the explanatory variables of agricultural carbon finance are 16.942, 7.052, and 1.926, respectively, while the minimum values are 0.965, 0.048, and 0.079, respectively, and the maximum values are 17.56, 146.92, and 100.33 times as much as the minimum values, respectively It can be found that the difference between the maximum value and the minimum value is large, indicating that there are large differences in the development of agricultural carbon financial innovation in different provinces. The mean value of per capita carbon emission of the explanatory variables is 13.254 tons/person, the maximum value is 128.945 tons/person, the minimum value is 0.145 tons/person, and the maximum value is 889.28 times of the minimum value, which indicates that the carbon emission reduction effect in most provinces and cities in China is relatively poor, and the effect of low-carbon development has not yet appeared.

Table 2. Descriptive statistics

Variable	Obs	Mean	Std.Dev	Min	Max
Pc	425	13.254	16.845	0.145	128.945
Lnpc	425	1.894	1.294	-1.768	5.374
Acs	425	2.341	1.254	0.965	16.942
Ace	425	0.654	1.169	0.048	7.052
Acfs	425	0.768	0.375	0.079	1.926
Lnpgdp	425	11.326	0.521	9.026	13.214
Ind	425	0.594	0.106	0.204	0.855
Tech	425	0.004	0.001	0.001	0.008
FDI	425	0.015	0.016	0.001	0.203
Inv	425	0.846	0.276	0.223	1.968
Human	425	0.014	0.023	0.000	0.147
Inf	425	3.695	3.041	0.483	16.845
Lninf	425	0.978	0.776	-0.765	2.842

4.2. *Unit root test*

In this paper, panel data of 30 provinces in China from 2014-2024 are selected for analysis. There exists a lagged period of carbon emission reduction development in the study to constitute the dynamic panel data. If the variable series are not smooth, it may bias the estimation results of the model. Therefore, it is necessary to conduct a smoothness test on the variables before the regression to check whether there is a unit root in the data, so as to avoid false regression or pseudo-regression on the results to ensure the reliability of the results and the stability of the data. This paper uses the LLC test (homogeneous unit root) and ADF-Fisher, IPS test (heterogeneous unit root) to carry out the corresponding test, the unit root test of each index is shown in Table 3, and the test results show that: each variable passes the LLC test, the IPS test and the ADF-Fisher test, which indicates that the panel data are smooth and can be further studied.

Table 3. Unit root test results

Variable	LLC test	ADF-Fisher test	IPS test
Pc	-6.067***	112.773***	-5.957***
Lnpc	-4.506***	97.333***	-6.511***
Acs	-5.338***	115.278***	-7.813***
Ace	-4.915***	118.139***	-6.101***
Acfs	-5.238***	109.834***	-6.809***
Lnpgdp	-8.058***	98.078***	-9.714***
Ind	-6.165***	116.813***	-7.538***
Tech	-8.198***	115.518***	-12.111***
FDI	-5.941***	97.228***	-6.132***
Inv	-7.847***	124.643***	-12.562***
Human	-4.817***	122.101***	-7.066***

Inf	-5.343***	112.216***	-10.044***
Lninf	-4.002***	110.466***	-6.923***

4.3. *Analysis of system GMM estimation results*

In this paper, the dynamic panel model is used, and the mixed least squares (OLS) and fixed effect (FE) can constitute the upper and lower limits of the parameter estimates, and the mixed least squares estimation (OLS) and fixed effect estimation (FE) are used to obtain the interval of the parameter estimates, and then the model is estimated by the systematic GMM method.

By regressing the dynamic panel model, the full sample OLS and FE regression results are then obtained as shown in Table 4. Among them, from model (1) to model (3) represent the regression results of mixed least squares estimation OLS, while model (4) to model (6) represent the regression results of fixed effects FE. The results show that when using agricultural carbon financial scale (Acs), agricultural carbon financial efficiency (Ace), and agricultural carbon financial structure (Acfs) to represent the level of agricultural carbon financial innovation and development, the models show that the lagged one period of the explanatory variable per capita carbon emissions (Lnpc) is significant at the 1% level in both the OLS estimation and the FE estimation, and then it can be judged that the lagged one period of the explanatory variable's parameter estimation coefficients should be within the intervals of 0.446 to 0.885, 0.458 to 0.882, and 0.443 to 0.911, respectively.

Table 4. OLS and FE regression results of model full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	FE	FE	FE
Lnpc	0.885***	0.882***	0.911***	0.446***	0.458***	0443***
	(60.025)	(60.048)	(59.648)	(15.344)	(15.684)	(15.287)
Acs	0.241***			0.026		
	(0.038)			(0.014)		
Ace		0.085			0.005	
		(0.096)			(0.031)	
Acfs			1.524***			0.472***
			(0.203)			(0.175)
Lnpgdp	10.056***	10.246***	10.023***	0.152	0.221	0.835
	(2.203)	(2.245)	(2.241)	(1.726)	(1.728)	(1.864)
Lnpgdp2	-0.415***	-0.432***	-0.402***	-0.018	-0.037	-0.037
	(0.113)	(0.115)	(0.108)	(0.084)	(0.084)	(0.087)
Ind	0.068	-0.705*	1.068**	-0.169	-0.224	0.265
	(0.435)	(0.422)	(0.468)	(0.248)	(0.245)	(0.294)
Tech	-14.958***	-12.687**	-14.725***	-9.846***	-9.054***	-7.526***
	(50.954)	(52.354)	(50.562)	(24.226)	(24.268)	(24.249)
FDI	-9.856***	-10.578***	-8.974***	-0.897	-0.915	-0.856
	(2.674)	(2.795)	(2.568)	(1.626)	(1.628)	(1.609)
Inv	-0.896***	-0.954***	-1.154***	-0.078	-0.082	-0.125*
	(0.156)	(0.158)	(0.152)	(0.077)	(0.078)	(0.079)
Human	-24.585***	-19.485***	-21.065***	-3.745	-3.426	-3.812
	(2.562)	(2.348)	(2.138)	(2.867)	(2.865)	(2.844)
Lninf	0.596***	0.582***	0.551***	0.263***	0.257***	0.189**
	(0.085)	(0.088)	(0.083)	(0.076)	(0.076)	(0.079)
Constant	-58.648***	-58.848***	-60.251***	0.596	0.298	5.124
	(11.678)	(11.964)	(11.267)	(8.065)	(8.092)	(8.241)

Ob	400	400	400	400	400	400
R2	0.925	0.925	0.925	0.627	0.627	0.627

So the next step is to estimate the model by applying the system GMM method, and its model regression results are shown in Table 5. As can be seen from Table 5, the estimated value of the lagged one period of the explanatory variable carbon emissions (Lnpc) is located within the range of the corresponding estimates above, and all of them are significant at the 1% level, which also indicates that the carbon emissions in the previous period do affect the carbon emissions in the current period, and there is a positive correlation between the two, i.e., China's carbon emissions have a cumulative, continuous, and dynamic, and the use of the dynamic panel model in this paper is also reasonable. The test result of AR(1) in the table is significant, while the test result of AR(2) is not significant, which indicates that the original hypothesis set by it cannot be rejected; the result of Sargan's test also indicates that the original hypothesis set by it cannot be rejected, so the parameter estimation is consistent and valid. From model (1) to model (3) in Table 5 represent the relevant regression results of the system GMM when the level of financial development is measured by financial size (Fs), financial efficiency (Fe), and financial intermediation development (Fi) respectively. The conclusions drawn are as follows:

1) There is a strong correlation between carbon emissions (Lnpc) and agricultural carbon financial innovation and development (Acd), and different measures of agricultural carbon financial development have different impacts on carbon emissions. For China's full sample, carbon financial scale (Acs), carbon financial efficiency (Ace), and carbon financial structure (Acfs) all have a strong negative correlation with carbon emissions, as shown by the fact that each unit increase in carbon financial scale, carbon financial efficiency, and carbon financial structure reduces per capita carbon emissions by 22.5%, 20.5%, and 24.5%, respectively, which suggests that the development of carbon financial innovations can indeed reduce carbon emissions, and the degree of reduction is more considerable. Moreover, the table shows that the parameter estimation of carbon financial scale is significant at 10% level, the parameter estimation of carbon financial efficiency is significant at 1% level, and the parameter estimation of carbon financial structure innovation is significant at 5% level.

2) The EKC relationship between economic growth (Lnpgdp) and carbon emissions (Lnpc) holds. The primary term coefficient of economic growth (Lnpgdp) in the table is greater than zero, while its secondary term coefficient is less than zero, i.e., there is an inverted U-shaped relationship between economic growth and carbon emissions, i.e., the EKC hypothesis is established.

3) The relationship between other variables and carbon emissions. Among them, the industrial structure (Ind) and carbon emissions are roughly positively correlated with each other. There is a negative correlation between technological progress (Tech) and carbon emissions, but the result is not significant. There is a negative correlation between the level of foreign investment (FDI) and carbon emissions, which indicates that the spillover effect of FDI in China can reduce carbon emissions. There is a positive correlation between the level of investment (Inv) and carbon emissions, which suggests that China consumes a large amount of fossil energy for fixed asset investment, which contributes to carbon emissions. There is a negative correlation between human capital and carbon emissions, which suggests that increasing the stock of human capital can expand the effects of technology and thus reduce carbon emissions. There is a negative correlation between the level of infrastructure (Lninf) and carbon emissions, which suggests that the effective construction of infrastructure can also reduce carbon emissions.

Table 5. System GMM regression results of model full sample

	(1)	(2)	(3)
	System GMM	System GMM	System GMM
Lnpc	0.635***	0.628***	0.675***
	(13.745)	(10.865)	(11.526)

Acs	-0.225*		
	(0.018)		
Ace		-0.205***	
		(0.036)	
Acfs			-0.245**
			(0.182)
Lnpgdp	-0.135**	-0.014**	-0.756**
	(1.745)	(1.736)	(1.798)
Lnpgdp2	0.005**	0.011**	0.035**
	(0.084)	(0.084)	(0.086)
Ind	0.362*	0.378*	0.032
	(0.235)	(0.228)	(0.289)
Tech	-9.458	-8.203	-2.068
	(25.926)	(25.987)	(26.345)
FDI	-0.196**	-0.197**	-0.195**
	(1.203)	(1.203)	(1.218)
Inv	0.025***	0.026**	0.061**
	(0.074)	(0.074)	(0.076)
Human	-2.035*	-2.176*	-1.086*
	(2.963)	(2.842)	(2.987)
Lninf	-0.078***	-0.075**	-0.005**
	(-0.072)	(0.072)	(0.075)
Constant	-1.623**	-0.852**	-3.942**
	(8.926)	(8.895)	(8.915)
AR(2)	0.834	0.725	1.163
	(0.426)	(0.487)	(0.274)
Sargan	32.956	34.478	30.623
	(0.356)	(0.284)	(0.469)
Observations	400	400	400
N	40	40	40

4.4. Robustness Tests

In order to ensure the robustness of the results and validate the previous conclusion that agricultural carbon financial innovation has a positive impact on carbon emission reduction, this paper will carry out the robustness test from two aspects: (1) 1% shrinking-tail treatment. In order to prevent the emergence of large fluctuations in the variables on the regression results, to verify the robustness of the results, so this paper on the continuous variables 1% shrinking tail treatment. As shown in column (1) of Table 6, the impact of agricultural carbon financial innovation (Acd) on carbon emissions (Lnpc) is significantly negative, with an impact coefficient of -0.245, so the conclusions of the GMM regression after the shrinking of the tails are consistent with the original regression conclusions. (2) Replacement of the measurement method. Change the measurement method of carbon emission, use principal component analysis to re-measure the carbon emission index, and passed the KMO test and Bartlett's spherical test, indicating that it can be measured by principal component analysis. As shown in column (2) of Table 6, the effect of agricultural carbon financial innovation on carbon emissions is significantly negative at the 1% level, indicating that agricultural carbon financial innovation has a facilitating effect on reducing carbon emissions. It is consistent with the conclusion drawn from the regression of the comprehensive indicator of carbon emissions measured using the entropy value method.

Table 6. Robustness test results

Variable	1% tail shrinkage	Substitution measurement
	(1)	(2)
Acd	-0.245***	-0.268***
	(-10.65)	(-4.95)
Lnpgdp	-0.086***	-0.092***
	(-6.12)	(-3.87)
Ind	-0.096***	-0.072***
	(-3.95)	(-1.34)
Tech	-0.152***	-0.185***
	(-3.59)	(-2.58)
FDI	-0.756***	-0.962***
	(-8.69)	(-4.87)
Inv	-0.623***	-0.874***
	(-6.74)	(-3.68)
Human	-0.385***	-0.425***
	(-8.45)	(-4.22)
Lninf	-0.296***	-0.348***
	(-4.85)	(-1.69)
Lnpc	-1.234***	-1.695***
	(-80.56)	(-72.15)
_cons	-0.426***	-0.512***
	(-4.62)	(-3.29)
N	400	400
AR(1)	0.001	0.003
AR(2)	0.425	0.624
Sargan	0.226	0.337

5. Conclusion

In order to explore the impact of agricultural carbon finance innovation and development on carbon emission reduction, this paper adopts systematic GMM estimation to construct an inquiry model of the two on the basis of analyzing the relevant theories of carbon finance and carbon emission, and selects research variables. Through empirical research, the relationship between the two is clarified.

The maximum values of agricultural carbon finance scale, carbon finance efficiency and carbon finance structure in agricultural carbon finance are 17.56, 146.92 and 100.33 times of the minimum value respectively, indicating that there are large differences in the development of agricultural carbon finance innovation in different provinces. The maximum value of per capita carbon emission is 889.28 times of the minimum value, indicating that most provinces and cities have poor carbon emission reduction.

Agricultural carbon financial scale, carbon financial efficiency, and carbon financial structure all have a strong negative correlation with carbon emissions, and per capita carbon emissions are reduced by 22.5%, 20.5%, and 24.5% for each unit increase in carbon financial scale, carbon financial efficiency, and carbon financial structure, respectively. The parameter estimates of carbon financial scale, carbon financial efficiency, and carbon financial structure are significant at the levels of 10%, 1%, and 5%, respectively. It indicates that the innovative development of agricultural carbon finance helps to reduce carbon emissions.

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