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Original Research

Does Agricultural Insurance Drive Variations in Carbon Emissions in China? Evidence from a Quasi-Experiment

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Abstract

To realize the great goal of attaining peak carbon in 2030 and carbon neutrality in 2060, agricultural carbon mitigation must be an essential activity in China. Policy-oriented agricultural insurance is accepted as an effective income guarantee and risk transfer tool, which can not only disperse the risk of agricultural operation but also guide green agricultural production. In this study, based on panel data from 2012 to 2018 in China, a multistage dynamic DID model is constructed to systematically explore the effect of policy-oriented agricultural insurance on green agricultural development, primarily to clarify the specific mechanism of the effect. The results show that agricultural carbon emission is increasing year by year and the implementation of policy-oriented agricultural insurance has a significant positive impact on reducing agricultural carbon emissions. We further find that the promotion effect of agricultural insurance on carbon emission reduction increases with the expansion of agricultural technicians and the decrease of agricultural chemical utilization. In terms of spatial heterogeneity, the impact of the policy-oriented agricultural insurance on reducing agricultural carbon emissions is stronger in central and western regions than in eastern regions. At the same time, this paper provides operational suggestions for low-carbon agricultural development and the formulation of relevant macroeconomic agricultural policies. Our findings support the positive effect of policy-oriented agricultural insurance and provide significant policy implications for agricultural carbon emission reduction and control actions in China and other countries.

Keywords: climate crisis, sustainable agricultural development, multistage dynamic DID model, policy implications, mechanisms

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Introduction

The climate is changing, and there is a broad consensus that the cause of that change is the accumulation of greenhouse gas (GHG) emissions causing climate-altering pollution, which already affects Earth's terrestrial and aquatic systems [1]. A significant cause of accelerated global warming is the quick progression of agriculture, which contributes 11.8% of total GHG emissions (or as much as 25%, including related land-use changes) [2]. As the world's largest developing country and the largest emitter of greenhouse gases, China is actively involved in international climate-change solutions, and its firm attitude towards mitigating GHG emissions has been generally acknowledged by the international community [3]. It has been suggested that low-carbon agricultural management should be adopted as a means of adapting to the climate crisis, solving the problem of passive impacts on agriculture-related events, and achieving sustainable agricultural development [4]. Agricultural insurance is considered to be a promising instrument for managing the increasing climate risks faced by smallholder farmers and accelerating low-carbon agricultural development [5]. Globally, governments spend billions of dollars subsidizing agricultural premiums, and global initiatives have committed significant funds to support agricultural insurance [6].

As a major agricultural producer in Europe, France's agricultural insurance has emerged since the middle of the 19th century. In 2004, France gradually carried out the pilot subsidies for multi-disaster agricultural insurance, and the agricultural insurance developed rapidly [7]. The US agricultural insurance adopts the government-led market operation mode. In 2019, the insured area of the insurance has reached 135.57 million hm^2, accounting for about 80% of the cultivated land area [8]. The Canadian agricultural insurance adopts the joint subsidy system of the federal government and local governments, which provides full subsidies for the operation and management expenses of insurance companies and 60% premium subsidies for farmers. According to statistics, 86% of the total premium was collected in high-income countries, while only 0.03% was collected in low-income countries [9]. However, since 2007, there has been a dramatic expansion of agricultural insurance in some developing countries, notably China, which has helped correct the imbalance [9]. Additionally, with China's entry into the WTO, agricultural support and protection policies required adaptation, and the government began to attach great importance to the role of agricultural insurance in supporting agriculture. Compared with some developed countries, China's agricultural insurance started late and the guarantee level is low, which is in the preliminary development stage. Therefore, the Chinese government implemented policy-oriented agricultural insurance (POAI) experiment in 2007 in six provinces, and the number of implementation provinces increased year by year. POAI refers to the market-oriented operation of insurance companies and direct physical and chemical cost insurance provided by the government for economic losses caused by natural disasters and accidents through policy support such as premium subsides [10]. Although a growing amount of positive evidence indicates that insurance can significantly improve the stability and sustainability of farmers' income [11], little research has been carried out concerning the systematic evaluation of the influences of POAI on low-carbon agricultural development.

Theoretically, agricultural insurance is supposed to contribute to agricultural output and low-carbon agricultural development in the following two ways: On the one hand, moral hazard and adverse selection under the agricultural insurance system reduce farmers' investment willingness, reduce their enthusiasm for chemical investment, and improve the agricultural ecological environment. On the other hand, agricultural insurance may encourage farmers to adopt green agricultural techniques, which will affect pesticide use and fertilization structure [12, 13]. Empirical studies and field trial results also support the theoretical prediction of agricultural insurance on green production [14, 15]. Therefore, the reduction of agricultural chemical input and the promotion of green technology may be expected to promote the development of green agriculture. Conversely, some researchers suggest that the long-term effects of insurance on agricultural decision-making and other indicators are quite weak [5]. Currently, there are few studies on the impact of POAI on agricultural carbon emissions, so we try to understand this effect with the help of Chinese agricultural data.

Difference in difference is a commonly used, quasi-experimental method of estimating the causal effects of specific public policies (such as the POAI mechanisms studied in this article). Since the implementation of public policy is usually not influenced by subject consciousness, the implementation of policy can be regarded as an exogenous "intervention" of the subject; therefore, the implementation of the policy can also be considered a quasi-experiment [16]. The fundamental purpose of the DID approach is to investigate comprehensively the differences amongst the differences both with and without and before and after the enforcement of certain policies [17]. The DID model estimates the net effect of policy implementation by comparing the differences independent variables between the experimental group and the control group before and after the implementation of such policies [18]. In recent years, an increasing number of scholars have applied the DID model to conduct causal analysis of public policy effects, with representative studies including Feng and Hu [19], Chen et al. [20] and She et al. [21].

Due to the different implementation periods of agricultural insurance policies in different provinces in China, the following three key questions were discussed based on the multi-stage dynamic DID model: (1) What is the impact of POAI on agricultural carbon emissions? (2) What is the mechanism of POAI on agricultural carbon emissions? (3) Does the impact of POAI show any spatial heterogeneity?

Theoretical Principle and Research Hypothesis

POAI and Agriculture Carbon Emissions

Developing green agriculture and transforming agriculture from high-carbon extensive development to green intensive development is an effective way to promote the sustainable development of agriculture [22]. Farmers are rational economic people, and their main purpose is to avoid risks and expand profits. As a result, the enthusiasm to use advanced technology and environmental protection equipment is low, which hinders the improvement of agricultural production efficiency and the choice of green technology [23]. However, agricultural insurance plays a role in resolving the dual risks of agriculture, which can improve the ability of farmers to resist risks by using green technologies and help reduce agricultural carbon emissions. Many researchers believe that agricultural insurance can reduce pesticide consumption [24], that is, agricultural insurance encourages farmers to accept more risk and get more benefits. However, chemical inputs are a significant source of agricultural carbon emissions, so crop insurance could help mitigate agricultural carbon emissions levels. Considering the changing trend of agricultural carbon intensity, we propose the following hypotheses based on existing research results:

H1: POAI can mitigate agricultural carbon emissions

Mechanism of POAI to Mitigate Agricultural Carbon Emissions

As a useful risk transfer policy, agricultural insurance subsidies influence carbon emission levels through multiple channels [25]. Agricultural insurance has the function of stabilizing farmers' income expectations, improving farmers' ability to resist risks by using agricultural protection facilities, and arousing farmers' initiative to adopt environmental protection equipment, thus contributing to alleviating agricultural carbon emission levels [26]. Secondly, the input of chemicals in agricultural production is closely related to the agricultural environment, and most of the agricultural carbon emission sources come from the excessive input of agricultural chemicals. Farmers who participate in agricultural insurance can usually obtain certain compensation after disasters, to effectively guarantee farmers' income and output and reduce farmers' attention and enthusiasm for farmland investment. Therefore, the increase in the scope and intensity of government-supported agricultural insurance subsidies will lead farmers to reduce factor inputs in agricultural production [27], which may contribute to reducing agricultural carbon emissions. Based on the above discussion, the second theoretical hypothesis is proposed in this study:

H2: POAI can reduce agricultural carbon emissions by improving technology levels and reducing chemical inputs.

Heterogeneous Effects of POAI on Agricultural Carbon Emissions

As a largely agricultural country, China has certain differences in resource endowment, geographical location, agronomic conditions, and economic environment among provinces, and the implementation of agricultural policies under different conditions may produce different effects. First, there are obvious regional differences in economic development between the eastern provinces and the central and western provinces, and the secondary and tertiary industries in the eastern region develop rapidly, while agriculture occupies a small share in its economic aggregate. However, the size of agriculture in the central and western regions is large, but agricultural technology is relatively backward and resource utilization efficiency is low, which may affect the implementation level of agricultural insurance. Second, the agricultural insurance subsidies set by the central government vary significantly from region to region in China. According to the Measures for the Administration of Central Agricultural Insurance Premium Subsidies, the central government subsidizes 40% of the central and western regions and 35% of the eastern regions. Therefore, for the eastern region, the implementation conditions of agricultural insurance policies may be worse than those in the central and western regions, and there may be a certain spatial heterogeneity in the policy effects of agricultural insurance. Based on the above views, the third hypothesis of this study is formulated as follows:

H3: The impact of POAI on agricultural carbon emissions is spatially heterogeneous.

Material and Methods

Difference-in-Differences Model (DID)

China's POAI policy uses a procedure of beginning with a pilot program before any promotion of the program, and the pilot time varies in different provinces. To this end, this study treats agricultural insurance policy as a quasi-natural experiment, using a multistage dynamic difference in difference model (DID) to identify the effects of agricultural insurance policies on agricultural carbon emission levels. The causal effects of the POAI policy can be estimated using the following models:

$$Y_{it} = \alpha + \beta Treat_{it} + \varphi \sum X_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i represents the province, t represents the year, and Y_{it} refers to the dependent variable, representing the agricultural carbon emission level of province i in t. In this study, per capita carbon emissions (Remission) are used to represent the degree of agricultural carbon emissions. Additionally, $Treat_{it}$ is a sorting dummy variable representing the core independent variable of this paper (POAI policy), which has a value of 1 if province i is a pilot area in year t and 0 otherwise; X_{it} represents a set of control variables at the provincial level, which will be elaborated on below. ε_{it} is a random perturbation term. Moreover, the DID method accepts the control of missing variables, and u_i and λ_i are added to the equation system to control the province fixed effect and time fixed effect, respectively. In Equation (1), coefficient β is the object in which we are interested, which is an important basis for evaluating the effectiveness of policy implementation. If this value is significant and negative at a certain statistical level, it confirms that POAI policies can effectively mitigate agricultural carbon emissions.

Selection of Related Variables

Agricultural carbon emissions are mainly produced by factors of production and other activities in production and planting. In 2007, IPCC proposed that it was practical to regard carbon emissions as the unintended output of agricultural production, and accurately reported the carbon sources and their emission coefficients in agricultural production [28], which have been widely used in academic articles. For a long time, the methods of calculating agricultural carbon emissions have been relatively rich, and this study draws on the research results of IPCC and the research results of predecessors [29, 30] to calculate agricultural carbon emission levels and uses per capita carbon emissions as a dependent variable to measure environmental pollution from agricultural production and farming. Equations (2)-(4) provide the calculation method, and the carbon source coefficient is shown in Table 1.

$$Emission_i = \sum E_{si} = \sum T_{si} \cdot \delta_s \tag{2}$$

$$Remission_i = E_i / TRP_i \tag{3}$$

$$\text{Intensity}_i = E_i / AAV_i \tag{4}$$

In Equation (2), $Emission_i$ represents the total agricultural carbon emission in province i, ΣE_{si} refers to the total carbon emission of various carbon sources in province i, T_{si} is the use of carbon emission sources s in province i, and δ_s is the carbon emission coefficient of s carbon emission sources. In Equation (3), $Remission_i$ represents the per capita agricultural carbon emission of province i (total agricultural carbon emissions divided by the rural population), and TRP_i refers to the total rural population of province i. Also, the robustness analysis below selects agricultural carbon emission intensity as the main dependent variable for estimation. In Equation (4), $CIAO_i$ represents the agricultural carbon emission intensity of province i (total agricultural carbon emissions divided by agricultural added value) and AAV_i represents the agricultural added value of province i.

Table 1. Agricultural carbon emission source, coefficient and reference sources.

Carbon source	Carbon emission coefficient	Reference source
Fertilizer	0.8956kg·kg^{-1}	ORNL[1]
Pesticide	4.9341kg·kg^{-1}	ORNL
Agricultural film	5.18kg·kg^{-1}	IREEA
Diesel	0.5927kg·kg^{-1}	IPCC
Plowing	312.6kg·km^{-2}	IABCAU
Irrigation	20.476kg·hm^{-2}	Dubey Laboratory, USDA[2]

[1] ORNL (Oak Ridge National Laboratory); IREEA (Institute of Resources Ecosystem and Environment of Agricultural, Nanjing Agricultural University); IPCC (Intergovernmental Panel on Climate Change); IABCAU (China Agricultural University School of Biology and technology).
[2] The carbon emission coefficient of agricultural irrigation is 25 kg/hm^2, but considering that only the fossil fuel demand of thermal power generation leads to indirect carbon emission, the average thermal power coefficient of 0.819 is added to the 25kg basis, and the final actual coefficient of agricultural irrigation is 20.476 kg/hm^2.

The binary variable formed by POAI implementation or not is the core independent variable of this paper. When province i is successfully piloted in year t, the value of $Treat_{it}$ in year t and the following years is 1; otherwise, the value is 0. Based on the Central Financial Agricultural Insurance Pilot Management Measures and the Implementation Notice of provincial Policy-oriented Agricultural Insurance from 2007 to 2012, the process of China's POAI policy is shown in Fig. 1, where different pilot years are marked by different colors.

Based on Fu et al. [31] and Lan et al. [32], we need to control other variables that affect agricultural carbon emissions, including actual agricultural disaster area (Damage), average years of education for farmers (Education), the proportion of the added value of primary industry (Status), per capita disposable income of farmers (Income), the proportion of financial support to agriculture (Finance), and industrial added value (Industry).

Actual agricultural disaster area (Damage). Natural disasters have a great impact on agricultural output, which will weaken farmers' enthusiasm for production and even hinder farmers from adopting green agricultural technologies, thus affecting agricultural carbon emissions.

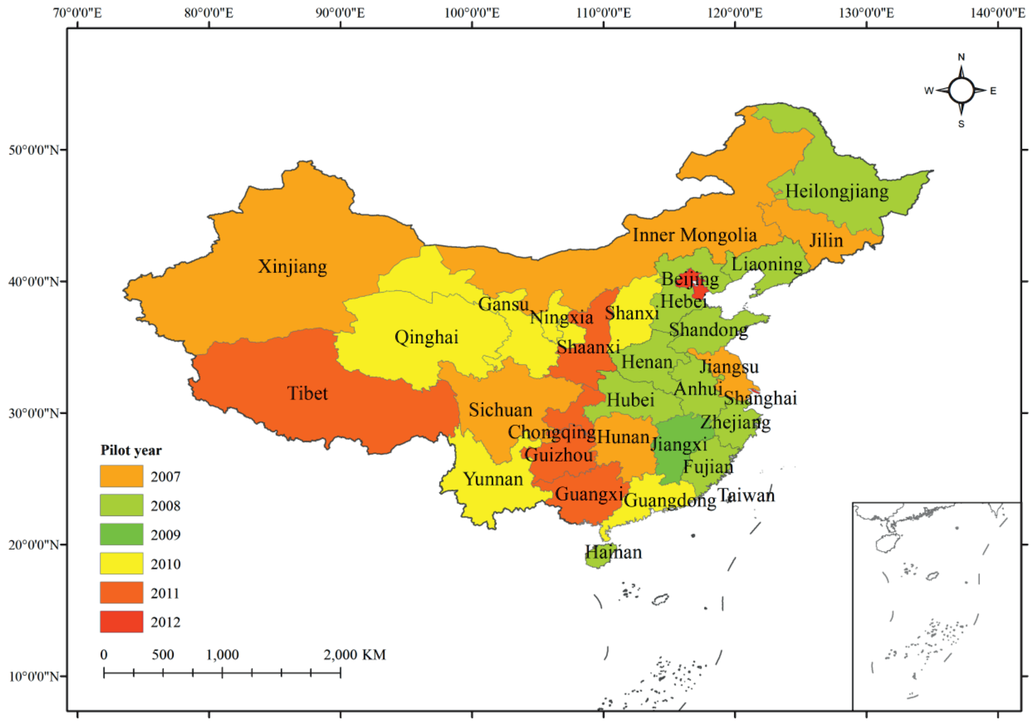

Fig. 1. Provinces distribution of China's policy-oriented agricultural insurance policy in different periods.

Average years of education in rural areas (Education). The higher the education level of farmers, the easier it is to accept the new technology, and the more green and intensive agriculture can be promoted.

The proportion of the added value of primary industry (Status). The proportion of the added value of the primary industry in GDP can reflect the development level of a regional agricultural economy. The larger the scale of agricultural production, the stronger the initiative of farmers to adopt green production technology, which is conducive to reducing the level of agricultural carbon emissions.

The higher the status of agriculture, the larger the scale of agricultural production, and the more likely farmers are to adopt advanced technologies, which help reduce the level of agricultural carbon emissions.

Per capita disposable income of rural residents (Income). The per capita disposable income of rural residents reflects the production and living standards of farmers. Only when the production income is stable, farmers will further consider the adoption of agricultural green technology. Therefore, this study uses the per capita disposable income of rural residents to measure the income level of farmers.

The proportion of financial support to agriculture (Finance) and industrial added value (Industry). We use the proportion of agricultural financial expenditure to the total financial expenditure to measure the support of local governments for agriculture. The more attention local governments attach to agriculture, the more conducive to the development and progress of local agricultural green production. At the same time, because the local industrial development level is related to the updating speed of agricultural technology and the production level of agricultural equipment, and determines the development of green agricultural production in the future, this paper also controls the added value of an industry.

Data Collection and Descriptions

To investigate the true effect and internal mechanism of agricultural insurance on agricultural carbon emissions, balanced panel data with 510 observations in 30 provinces from 2002 to 2018 were used. Data concerning agricultural insurance premium income and agricultural insurance compensation were collected from the "China Insurance Yearbook", and other data were collected from the "China Rural Statistical Yearbook", "China Statistical Yearbook", and "Economy Prediction System database and China Stock Market & Accounting Research database". To reduce heteroscedasticity, logarithmic processing was performed on the dependent variables. Meanwhile, this paper adopts the price index of 2002 as a base period to adjust the price of corresponding variables from nominal quantity to actual quantity, to meet modelling needs. Table 2 provides basic definitions and descriptive statistics for the variables. We use Stata (version 15.0) in this research to run the analysis. The statistical tests are two-sided, and the p-value tells us if the result is statistically significant. P values of <0.1 (*), <0.05 (**) and <0.01 (***) are considered statistically significant.

Table 2. Variable definitions and descriptive statistics.

Variables	Definitions	Mean	SD	Min	Max
Dependent Variable					
Remission	Per capita agricultural carbon emissions	1.262	0.616	0.273	3.672
Intensity	Agricultural carbon intensity	5.594	1.623	1.699	10.889
Independent Variable					
Treat	Province i is an agricultural insurance pilot area in year t and takes the value 1, otherwise it is 0				
Other variables					
Damage	Actual affected area of crops	1.162	1.047	0.000	7.394
Education	Average years of education in rural areas	7.718	0.599	6.061	9.912
Status	Proportion of added value of primary industry in GDP	11.664	6.262	0.320	37.900
LnIncome	Natural logarithm of rural per capita disposable income	8.718	0.676	7.306	10.321
Finance	Proportion of fiscal support to agriculture in fiscal expenditure	0.864	0.443	0.062	1.897
LnIndustry	Natural logarithm of industrial added value	8.177	1.177	4.428	10.536
Compensation	Actual compensation amount of agricultural insurance	0.413	0.625	0.000	4.325
Technician	Number of agricultural technicians	2.216	1.230	0.219	5.699
Fertilizer	Fertilizer consumption	0.179	0.140	0.007	0.716
Pesticide	Pesticide consumption	0.542	0.430	0.016	1.735

Results

Analysis of POAI on Agricultural Carbon Emission Intensity

In this study, a multistage dynamic DID model was used to analyze the impact of agricultural insurance pilot policies on agricultural carbon emissions. Without controlling variables, column (1) of Table 3 presents the true effect of agricultural insurance on per-capita agricultural carbon emissions. The coefficient of the core independent variable is significantly negative, which preliminarily verifies the positive impact of agricultural insurance on agricultural carbon emissions. Further, after the equation controls the disaster area, education level, agricultural support level, agricultural status and other factors, the coefficient sign of the Treat variable (binary dummy variable of agricultural insurance pilot) in column (2) of Table 3 is still significantly negative, proving that the policy can effectively alleviate per-capita agricultural carbon emissions, and the results in Table 3 are relatively robust. Additionally, according to the result of the Treat coefficient, when other variables remain unchanged, the per capita agricultural carbon emissions of pilot provinces are reduced by 10.6 percentage points on average compared with non-pilot provinces, which is significant at the level of 1%. Therefore, the empirical results confirm that China's current agricultural insurance policy does play a role in mitigating agricultural carbon emissions, which is consistent with hypothesis 1.

Combined with the coefficients of the control variables, it can be obtained that the coefficient of farmers' average years of education (Education) is negative and significant at the 5% level, indicating that the higher the education level of farmers, the more obvious the effect of mitigating agricultural carbon emission level. Meanwhile, the coefficients of agricultural disaster degree (Damage), agricultural output value ratio (Status), and industrial added value (Industry) are all negative, indicating that the more serious the agricultural disaster degree, the higher the status of agriculture or the higher the level of industrial development, the lower the level of agricultural carbon emissions. Additionally, the coefficient of farmers' per capita disposable income (Income) and financial support to agriculture (Finance) are significantly positive, confirming that the increase in farmers' income and agricultural support will increase the level of agricultural carbon emissions.

Robustness Analysis: Parallel Trend Test and Placebo Test

Parallel Trend Test

This study systematically explores the real effects of policy-based agricultural insurance pilot programs on agricultural carbon emissions. However, this approach is valid on the premise that there should be no significant difference in agricultural carbon emission levels between the pilot and non-pilot groups in the

Table 3. Baseline regression results of POAI on agricultural carbon emissions.

Independent Variable	Dependent Variable: Remission[1]	
	(1)	(2)
Treat	-0.102**[2]	-0.106***
	(0.042)	(0.039)
Damage		-0.003
		(0.014)
Education		-0.112**
		(0.053)
Status		-0.005
		(0.008)
LnIncome		1.483***
		(0.212)
Finance		0.480***
		(0.079)
LnIndustry		-0.092
		(0.081)
Constant	1.322***	-10.346***
	(0.027)	(1.743)
Province FE	YES	YES
Year FE	YES	YES
Observations	510	510
R-squared	0.862	0.898

[1] Remission (Per capita agricultural carbon emissions); Damage (Actual affected area of crops); Education (Average years of education in rural areas); Status (Proportion of added value of primary industry in GDP); LnIncome (Natural logarithm of rural per capita disposable income); Finance (Proportion of fiscal support to agriculture in fiscal expenditure); LnIndustry (Natural logarithm of industrial added value).

[2] The standard errors adjusted by province-year clustering are in brackets; ***, ** and * indicate significance at the levels of 1%, 5% and 10%, respectively.

absence of the external influence of the agricultural insurance pilot. Therefore, referring to the parallel trend test method of Beck et al. [33], this study constructs the following bidirectional fixed effect model with the help of the event study method for testing:

$$Y_{it} = \alpha + \beta_1 Treat_{it}^{-8} + \beta_2 Treat_{it}^{-7} + \cdots + \beta_{16} Treat_{it}^{8} + u_i + \lambda_t + \varepsilon_{it} \tag{5}$$

In Equation (4), $Treat_{it}^{J}$ is the binary dummy variable based on the pilot time of provincial policies. When the province is in the J th year before the pilot, $Treat_{it}^{-J}$ is assigned a value of 1; otherwise, the value is 0. When it is in the J th year after the pilot, $Treat_{it}^{J}$ is assigned the value of 1; for other cases, the value is 0. In addition, to make full use of the sample variability, data of $J \leq -8$ were included in –8, data of $J \geq 8$ were included in 8, and the meanings of other variables remained unchanged. β_1 to β_8 refers to the effects within 1 to 8 years before the agricultural insurance pilot, and β_9 to β_{16} refers to the effects within 1 to 8 years after the agricultural insurance pilot.

Fig. 2 reveals the estimated results of β within the 95% confidence interval, and we find that the estimation coefficients from β_1 to β_7 are around 0 and are not significant, confirming that there is no significant trend difference between a pilot and non-pilot provinces before the policy pilot, which satisfies the hypothesis of parallel trends. However, the slightly significant reason for β_8 maybe the predictability of policy and the advanced preparation of farmers. In addition, by observing the coefficients of the core independent variables after the policy pilot, the dynamic effect of policy implementation can be derived. As shown in Fig. 2, per capita agricultural carbon emissions began to decline after the implementation of the policy, and this effect continued to accumulate in the following years, indicating that POAI continued to reduce agricultural carbon emissions, and the policy had a cumulative dynamic effect.

Placebo Test

To confirm that the above empirical conclusions are not driven by unobservable variables, this paper refers to Cai et al. [34] method for placebo testing and generates "pseudo-policy dummy variables" by randomly allocating trial time. Specifically, the time points from 2007 to 2012 were randomly selected as the pilot time of agricultural insurance in 30 provinces to generate "pseudo policy dummy variables" and 1000 random samples, and repeated regression 1000 times according to Equation (1). Fig. 3 intuitively shows the coefficient estimated value and kernel density curve of 1000 times of "pseudo benchmark regression", in which the x-axis refers to the size of the "pseudo-policy dummy variable" coefficient estimate, the y-axis is the kernel density value, and the p-value, the blue dot is the corresponding p-value, the curve represents the kernel density distribution of the estimated coefficient, and the x-value of the vertical dashed line is the estimated coefficient of the true benchmark regression. It can be obtained that the estimated coefficients of the pseudo-dummy variable (Treat) are mostly distributed around zero and the p-value is greater than 0.1. Furthermore, the estimated value of the true baseline regression is significantly different from the coefficient mean of the pseudo-regression, which fully verifies

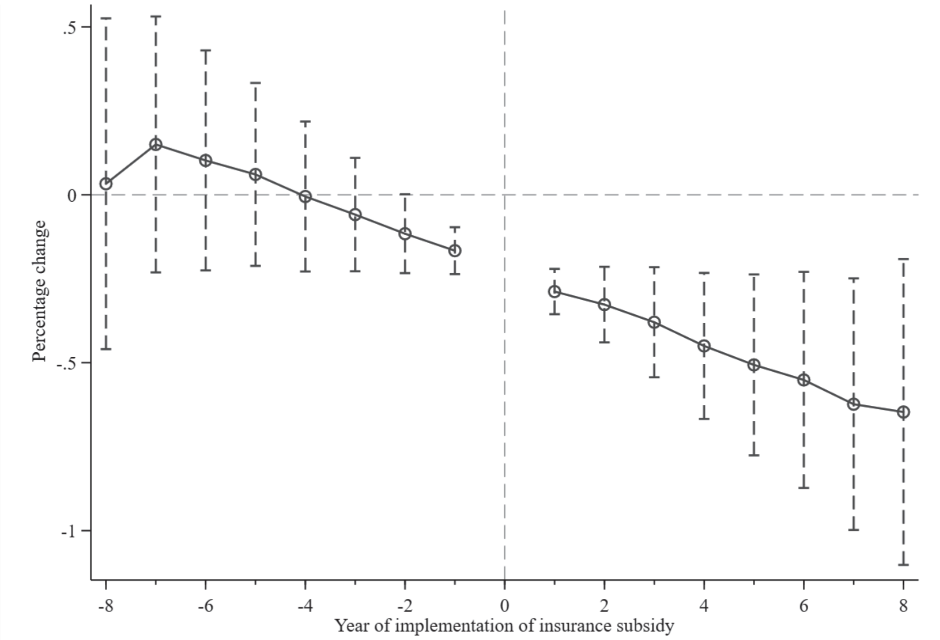

Fig. 2. The dynamic impact of POAI on per capita agricultural carbon emissions.

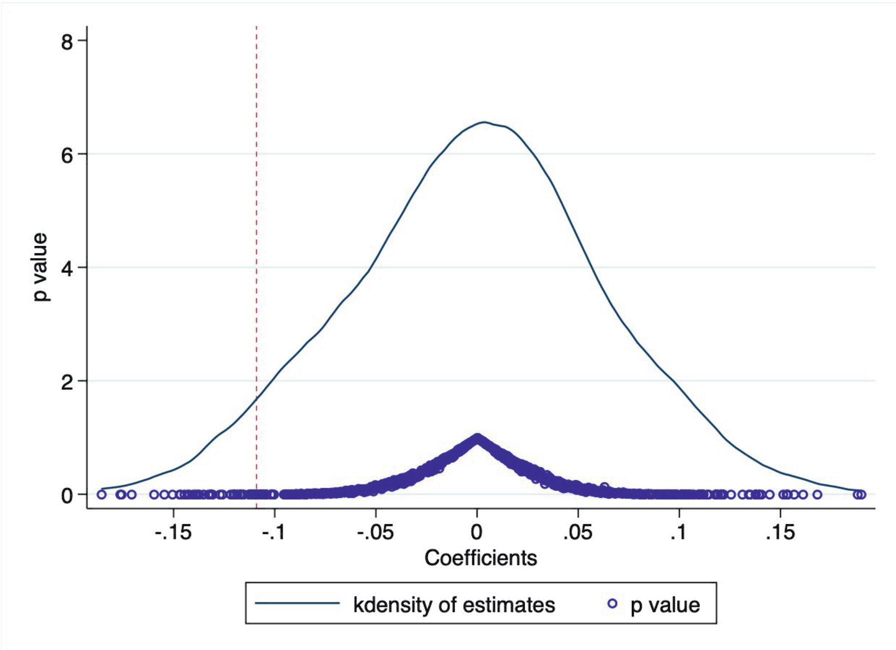

Fig. 3. A nuclear density map on a placebo test.

that the causal effect of POAI on agricultural carbon emissions is not caused by other unobtainable factors.

Other Robustness Tests

This section adopts a variety of test forms to further ensure the credibility of the empirical conclusions. First of all, in column 1 of Table 4, agricultural carbon emission intensity is taken as a proxy variable of agricultural carbon emission level, rather than per capita carbon emission. The result showed that the estimate of Treat was still significantly negative despite the substitution of the core independent variable, confirming the carbon reduction effect of agricultural insurance. Secondly, concerning the "quasi-multiplier method" proposed by Qian and Nunn [35], the actual compensation amount of agricultural insurance is replaced by the pilot dummy variable to measure the implementation intensity of insurance subsidies, and the interaction between the actual compensation amount of agricultural insurance and the virtual variable is added to the regression. As shown in Column 2

Table 4. Additional robustness tests of POAI on agricultural carbon emissions.

Independent Variable	Dependent Variable: Intensity[1]		Remission	
	(1)	(2)	(3)	(4)
Treat	-0.166**[2]			-0.119***
	(0.075)			(0.037)
Treat*Compensation		-0.231**		
		(0.100)		
Treat1			-0.212	
			(0.137)	
Compensation		0.547**		
		(0.247)		
Constant	15.838***	-9.362***	-10.495***	-7.577***
	(5.639)	(1.587)	(1.705)	(1.662)
Control variable	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	510	510	510	509
R-squared	0.847	0.911	0.902	0.898

[1]Intensity (Agricultural carbon intensity); Remission (Per capita agricultural carbon emissions); Compensation (Actual compensation amount of agricultural insurance); Treat*Compensation (Interaction terms between the actual compensation amount of agricultural insurance and the pilot dummy variable); Treat1 (Dummy variables one years ahead of the pilot time).
[2] The standard errors adjusted by province-year clustering are in brackets; ***, ** and * indicate significance at the levels of 1%, 5% and 10%, respectively.

of Table 4, the interaction coefficient is significantly negative, indicating that carbon emissions per capita are declining as insurance benefits gradually increase. Thirdly, column 3 of Table 4 makes a counterfactual test of changing the point at which the policy occurred. After randomly implementing the POAI policy one year in advance, it is found that the estimation result of the core independent variable coefficient is no longer significant, indicating that the advance of the agricultural insurance pilot will not exert a carbon emission reduction effect. Finally, given the problem of missing variables, all control variables are lagging by one period. Column 4 of Table 4 shows the results, and agricultural insurance still significantly weakens agricultural carbon emissions. Compared to Column 2 of Table 1, the estimate of Treat changed from -0.106 to -0.119 and was signed at the 1% level, further validating the robustness of the baseline results. In summary, the robustness tests provide sufficient empirical support for Hypothesis 1.

Mechanism Analysis of POAI for Reducing Agricultural Carbon Emissions

Farmers' adoption of new agricultural technologies is largely affected by the level of funds and risk tolerance, while agricultural insurance plays a role in dispersing risks and stabilizing the source of funds, and insured farmers are more inclined to update agricultural technologies and adopt environmentally friendly and efficient equipment, thereby increasing the demand for agricultural technical talents. Agricultural technicians, as guides in agricultural production, encourage insured farmers to adopt environmentally friendly technologies that may help reduce agricultural carbon emissions. This section explores whether the mitigation effect of agricultural insurance on agricultural carbon emissions is due to agricultural technicians through cross-econometric models. Moreover, China is the world's largest pesticide consumer (Ministry of Agriculture of China, 2011), and up to 40% of agricultural film, 60% of fertilizer and 70% of pesticide residues are left in the soil every year, causing serious damage to the agricultural ecological environment. Therefore, this study examines whether agricultural insurance reduces agricultural chemical inputs (mainly the consumption of pesticides and fertilizers) due to moral hazard and substitution effects, thereby having a positive effect on agricultural carbon emissions.

Table 5 examines the effects of agricultural insurance policies on per-capita agricultural carbon emissions after two mechanism variables are added

Table 5. Mechanism analysis of POAI on agricultural carbon emission.

Independent Variable	Dependent Variable: Remission[1]			
	(1)	(2)	(3)	(4)
Treat	-0.207***[2]	-0.201***	-0.170***	-0.180***
	(0.064)	(0.054)	(0.046)	(0.044)
Treat*Technician	-0.059**	-0.066**		
	(0.029)	(0.031)		
Technician	-0.035	-0.073		
	(0.052)	(0.048)		
Treat*FP			-0.034***	-0.069**
			(0.007)	(0.031)
FP			1.029***	0.584***
			(0.115)	(0.112)
Constant	1.384***	-8.958***	0.602***	-9.076***
	(0.124)	(1.771)	(0.078)	(1.634)
Control variable	NO	YES	NO	YES
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	510	510	510	510
R-squared	0.871	0.899	0.889	0.906

[1]Remission (Per capita agricultural carbon emissions); Technician (Number of agricultural technicians); Treat*Technician (Interaction term between the number of agricultural technicians and the pilot dummy variable); FP (Total amount of pesticide and fertilizer used); Treat*FP (Interaction terms between total pesticide and fertilizer use and experimental dummy variables);
[2] The standard errors adjusted by province-year clustering are in brackets; ***, ** and * indicate significance at the levels of 1%, 5% and 10%, respectively.

to the regression. First, the regression results of Mechanism 1 are shown in Columns 1 and 2 of Table 5. It can be obtained that the estimated coefficient of the number of agricultural technicians (Technician) is negative and significant, regardless of whether other variables are controlled or not, and the coefficient of Treat*Technician is also negative, indicating that POAI can reduce the per-capita agricultural carbon emissions by increasing the number of agricultural technicians, verifying the effectiveness of the mechanism1. Second, the regression results of Mechanism 2 are shown in Columns 3 and 4 of Table 5. We found that the estimated coefficient of FP was significantly positive and the Treat *FP coefficient was significantly negative, regardless of whether other variables were controlled, demonstrating that POAI mitigated agricultural carbon emissions by reducing pesticide and fertilizer consumption, and Mechanism 2 was validated.

Heterogeneity Analysis: Differences in the Eastern, Central and Western Regions

The mitigation effect of agricultural insurance on agricultural carbon emissions is demonstrated above. However, due to differences in institutional conditions and insurance implementation among provinces, we hypothesized that this effect might be spatially heterogeneous and validated the hypothesis through group regression. The main estimates are shown in Table 6, where the Treat estimate for the eastern region is not significant, while the carbon reduction effect of the corresponding agricultural insurance on the central and western regions is negative and significant at the 5% level. At the same time, the regression coefficients in columns (2) and (3) of Table 6 show that the agricultural insurance policy reduces the per capita agricultural carbon emissions by 12.1% and 11.9% in western and central China respectively, and the effect is indeed more obvious than that in the eastern region. Through the above group test, it is confirmed that there is indeed a spatial heterogeneous effect of agricultural insurance policy, and hypothesis 3 is reliable.

Discussion

China is one of the countries with the most frequent natural disasters and losses in agriculture, especially since the 1990s, both in terms of the frequency of disasters and the extent of losses, these events have become more and more serious [36]. The accelerated deployment of POAI in China has

Table 6. Heterogeneity analysis results: differentiation in Eastern, Central and Western Region.

Independent Variable	Dependent Variable: Remission[1]		
	East	West	Middle
Treat	-0.093	-0.121**[2]	-0.119**
	(0.048)	(0.056)	(0.051)
Damage	-0.044	0.083*	0.003
	(0.029)	(0.043)	(0.010)
Education	-0.193***	-0.002	-0.323***
	(0.071)	(0.063)	(0.095)
Status	-0.052***	-0.017	-0.001
	(0.010)	(0.021)	(0.011)
LnIncome	1.037***	1.046	1.408***
	(0.318)	(0.699)	(0.302)
Finance	0.170*	0.690***	0.499***
	(0.099)	(0.223)	(0.140)
LnIndustry	0.349**	0.113	-0.235
	(0.141)	(0.164)	(0.143)
Constant	-9.128***	-8.912	-6.806**
	(3.174)	(5.730)	(2.735)
Province FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	187	187	136
R-squared	0.877	0.906	0.970

[1]Remission (Per capita agricultural carbon emissions); Damage (Actual affected area of crops); Education (Average years of education in rural areas); Status (Proportion of added value of primary industry in GDP); LnIncome (Natural logarithm of rural per capita disposable income); Finance (Proportion of fiscal support to agriculture in fiscal expenditure); LnIndustry (Natural logarithm of industrial added value).

[2] The standard errors adjusted by province-year clustering are in brackets; ***, ** and * indicate significance at the levels of 1%, 5% and 10%, respectively.

played a key role in improving the risk prevention ability of Chinese agriculture, diversifying agricultural risks, stabilizing the agricultural market and accelerating the construction of modern agriculture. Referring to the 2019 IPCC Special Report on Climate Change and Land, greenhouse gas emissions from agricultural activities amounted to the equivalent of 10.8 to 19.1 billion tons of CO_2 between 2007 and 2016, representing 21% to 37% of global greenhouse gas emissions. In the context of China's commitment to attaining peak carbon emissions by 2030 and achieving carbon neutrality by 2060, part of the burden of carbon reduction should fall on China's agriculture sector.

Multistage dynamic DID model and provincial balanced panel data were applied to explore the environmental effects of agricultural insurance in this study. Both empirical analysis and robustness tests confirm that POAI does contribute to the mitigation of agricultural carbon emissions, with per capita agricultural carbon emissions in pilot provinces falling by 10.6% on average compared to non-pilot provinces, consistent with our guess. As some scholars have suggested, although agricultural insurance is designed for non-environmental purposes, it may also affect the environmental externalities of agriculture by influencing the use of land, fertilizers and pesticides [37]. This phenomenon may be caused by moral hazard and adverse selection, strengthening the substitution relationship between insurance and factor input, thus encouraging farmers to use inputs that increase risk and reduce inputs that reduce risk, which has a certain impact on the farmland environment.

Although POAI policies can be effective in reducing carbon intensity, the underlying mechanisms need to be clarified. Hypothesis 2 proposes that POAI pilot policy reduce agricultural carbon emission intensity by weakening agricultural chemical input and expanding the number of agricultural technicians, both of which pass the mechanism test. First, most of the contribution to agricultural carbon emissions comes from agricultural chemicals, so reducing the consumption of agricultural chemicals (pesticides and fertilizers) will make a direct positive contribution to agricultural carbon emissions. Han et al. [38] verified with survey data from 8 provinces in China that agricultural insurance significantly weakens pesticide use intensity, which is consistent with our conclusions. Second, the increase of agricultural technical personnel can better guide farmers to rationally use efficient and safe fertilizers, low-toxicity and low-residue pesticides, and green production technologies, and effectively reduce agricultural carbon emissions. Compared with uninsured farmers, insured farmers are more inclined to change their agricultural production behavior, which is due to the risk transfer effect and stable income effect of agricultural insurance, thus improving the agricultural production environment [39]. Carter et al. [40] confirmed with the help of research data that agricultural insurance enhanced the risk resistance ability of farmers who adopted environmental protection technology and could promote green agricultural production, further confirming our results.

In addition, considering the characteristics of insurance plans and the great differences in agricultural risk levels in different regions, the overall effects of crop insurance will naturally vary greatly. The study verified hypothesis 3 through heterogeneity analysis. The results of spatial heterogeneity analysis show that the carbon reduction effect of agricultural insurance in eastern China is not as good as that in central and western China. The reason for this result may be that the central and western regions are dominated by large agricultural provinces, and the promotion of agricultural insurance in these regions has significantly promoted agricultural risk resistance, thus accelerating the update of agricultural environmental protection technology and the substantial reduction of chemical consumption [41]. Meanwhile, the dynamic effect trend in the robustness test confirmed that the mitigation effect of agricultural insurance on carbon emissions increased year by year, which strengthened the necessity for long-term implementation of the policy.

Conclusions

The transformation of the traditional agricultural production mode of self-sufficiency and diversified operation to the green and intensive modern agricultural production mode is an inevitable trend of agricultural development, and it is also an inevitable choice to improve agricultural production efficiency and the competitiveness of agricultural product markets. Based on balanced panel data from 30 provinces in China from 2002 to 2018, this study uses a multistage dynamic DID model to explore the "net effect" of POAI on agricultural carbon emissions. First of all, the study found that agricultural insurance can effectively curb agricultural carbon emissions, and the carbon emission intensity of the implementation provinces decreased by 10.6% on average, which is of great significance for ensuring farmers' income, improving agricultural productivity, realizing agricultural sustainable development and green agricultural economy. Secondly, the inhibition effect of agricultural insurance on agricultural carbon emissions is mainly due to the substantial reduction of pesticide and fertilizer inputs and the increase of agricultural technical personnel. Thirdly, the study further verified that agricultural insurance policies have more significant carbon reduction effects in central and western provinces, indicating the necessity of implementing differentiated agricultural insurance policies.

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Conflict of Interests

The authors declare no conflict of interest.

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