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CAN CARBON TRADING CATALYZE ECOLOGICAL CIRCULAR AGRICULTURE? QUASI-EXPERIMENTAL EVIDENCE FROM CHINA'S REGIONAL POLICY PILOTS

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ABSTRACT

Ecological circular agriculture is a necessary choice for sustainable agricultural development. It is crucial for alleviating resource-environmental pressures and balancing ecological and economic progress. Within this context, the role of carbon trading policy is significant, as it acts as a catalyst in promoting the vitality of ecological circular agriculture. However, there is a dearth of research on how carbon trading affects the development of ecological circular agriculture. Therefore, this study aims to fill this gap by examining the impact of carbon trading policy on ecological circular agriculture and its underlying mechanisms. Panel data from 30 provincial-level administrative regions in China spanning 2006–2021 was used to construct a multidimensional index for ecological circular agriculture and apply a difference-in-differences (DID) approach. The findings reveal that carbon trading policy can enhance ecological circular agriculture in pilot provinces (municipalities) by 3.5 %, primarily through improved ecological technology and agricultural carbon productivity to drive the green transformation of agriculture. The effects are most pronounced in the western Chinese region and areas with stronger agricultural labor productivity. This research improves the understanding of carbon trading mechanisms in agricultural systems and provides insights for designing effective carbon trading mechanisms.

Keywords: sustainable agriculture, carbon trading policy, difference-in-differences (DID) model, mechanism analysis.

INTRODUCTION

Ecological circular agriculture is a production approach focused on the cyclic utilization of agricultural resources. It minimizes resource waste and environmental pollution by establishing closed-loop material circulation systems (Podger *et al*., 2016). Research demonstrates its significant impacts on agricultural sustainability, ecological integrity, and public health (Yue *et al*., 2022; Wang *et al*., 2025). However, ecological circular agriculture in China faces more acute challenges than developed nations, with the excessive application of chemical fertilizers and pesticides remaining prevalent in routine farming practices (Hu and Liu, 2024).

In 2023, the fertilizer use intensity of China was recorded at 390.4 kg ha^{-1} and pesticide use intensity at 6.2 kg ha^{-1} (NBS, 2024). The fertilizer use intensity was significantly higher than the globally recommended safe level of 225 kg ha^{-1}. Moreover, pesticide overuse leads to the migration of residues into water systems and food chains through soil and rainwater, endangering soil safety, ecosystems, and human health (Sun *et al*., 2012). These practices have caused soil compaction, acidification, microbial community disruption, and fertility degradation (Qi *et al*., 2020), directly impairing crop growth and agricultural product quality (Cheng *et al*., 2025). Therefore, to achieve sustainable agricultural development and the health and well-being of residents, it is necessary to actively promote the development of ecological circular agriculture.

Previous studies indicate that the development of ecological circular agriculture is influenced by multiple factors, including agricultural technology, practitioner expertise, market demand, and policy frameworks (Pretty *et al*., 2018; Bwambale *et al*., 2022; Springmann and Freund, 2022; Shehawy and Ali Khan, 2024; Sasaki, 2025). Advanced ecological techniques in agricultural technology are important, like precision irrigation and biological pest management (Bwambale *et al*., 2022; Rad, 2025). Practitioner expertise is also critical, as farmers' awareness and knowledge affect the adoption of circular practices, while training, age, and regional contexts further shape behaviors (Pretty *et al*., 2018; Velasco-Muñoz *et al*., 2021; Wen *et al*., 2024).

Market demand is a key driver, with factors such as consumer health consciousness and government procurement accelerating the transition (Shehawy and Ali Khan, 2024; Liu *et al*., 2024b). Macro-level policies include land use planning, subsidies, and taxation. Land policies allocate resources, subsidies ease producers' financial constraints (Springmann and Freund, 2022), and taxation discourages pollution. Existing studies have explored determinants from government, technology, personnel, and market perspectives; at the policy level, they cover land use, subsidies, and taxation. However, the impact of carbon trading policy, which serves as a mandatory and guiding regulatory instrument, on ecological circular agriculture has yet to be evaluated. Additionally, its influence on the internal mechanisms of ecological circular agriculture remains unclear.

To narrow the gap, this study evaluates the efficacy of carbon trading policy in promoting ecological circular agriculture and investigates its underlying mechanisms, aiming to provide theoretical insights and practical guidance for sustainable agricultural transitions. Specifically, it makes three contributions. First, it constructs a four-dimensional index system covering resource recycling, low-carbon production technologies, ecological benefits, and economic sustainability, providing a quantitative framework for assessing ecological circular agriculture development and addressing the lack of standardized evaluation tools. Second, by using difference-in-differences (DID) and propensity score matching (PSM) methodologies, it provides empirical evidence demonstrating the causal relationship between carbon trading policy and the advancement of ecological circular agriculture. Third, it clarifies policy mechanisms by identifying ecological technology adoption and agricultural carbon productivity enhancement as pathways, examining heterogeneous effects across regions and production structures. These insights allow for region-specific policy customization and adaptable implementation of carbon trading mechanisms.

MATERIALS AND METHODS

Research hypotheses

Theoretically, the carbon trading policy is grounded in the theory of externalities (Marshall, 2013), which argues that environmental pollution stems from the divergence between private and social costs. Agricultural production often produces negative externalities such as greenhouse gas emissions and resource depletion. Carbon trading internalizes these externalities by assigning and trading emission rights (Zeng *et al.*, 2024), using price signals to encourage emission reduction and resource efficiency. This market-based mechanism aligns private interests with social environmental goals, fostering the transition toward ecological circular agriculture (Nsabiyeze *et al.*, 2024). The comprehensive theoretical framework and the influence mechanism of carbon trading policy on ecological circular agriculture are illustrated (Figure 1).

First, by setting emission caps and creating tradable permits, carbon trading provides direct economic incentives for emission reduction. Agricultural producers can gain

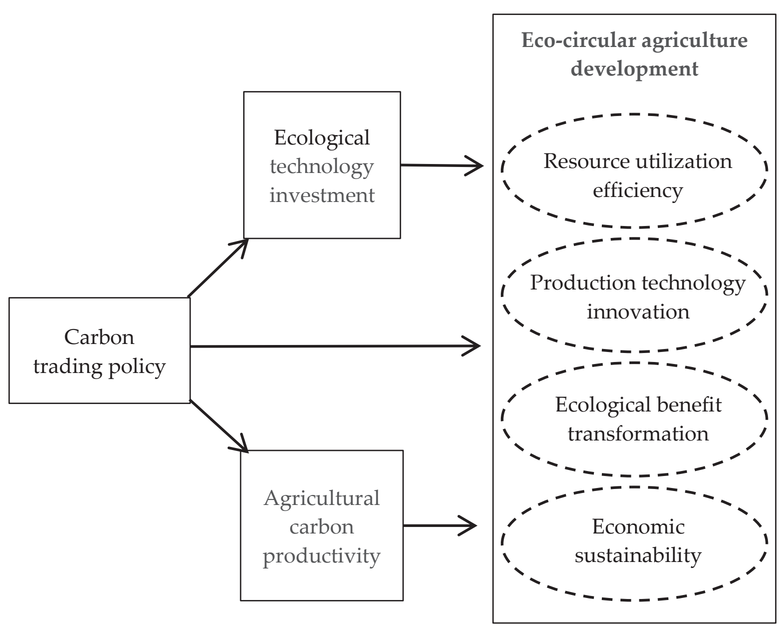

Figure 1. Influence mechanism of carbon trading policy on ecological circular agriculture (ECA).

financial returns by adopting eco-friendly practices or participating in emission reduction projects (Guo *et al.*, 2020), thereby promoting waste recycling and resource utilization in circular systems (Waldén *et al.*, 2020). Carbon trading helps reduce abatement costs and improve agricultural resource efficiency, driving ecological circular agriculture development. Consequently, it was proposed that:

H_1: Carbon trading policy exerts a statistically significant positive effect on the development of ecological circular agriculture.

Second, under carbon constraints, producers face stronger pressure to innovate. According to the Porter Hypothesis (Porter and van der Linde, 1995), properly designed environmental regulations can induce technological innovation that enhances both productivity and sustainability. By monetizing emission reductions, carbon trading stimulates investment in ecological technologies such as precision fertilization, biochar production, and manure treatment (Chen *et al.*, 2014), thus improving resource efficiency and reducing agricultural emissions. Therefore, it was proposed that:

H_2: Carbon trading policy stimulates the development of ecological circular agriculture by augmenting investments in ecological technologies.

Third, improving agricultural carbon productivity is essential for advancing low-carbon and efficient agricultural transformation, a key indicator of ecological circular agriculture (Rehman *et al.*, 2022). The adoption of ecological technologies such as precision fertilization and resource recycling reduces carbon emissions per unit of output and enhances resource efficiency. Meanwhile, carbon trading promotes industrial synergy by linking green consumption with low-carbon production, encouraging producers to adopt cleaner technologies for higher returns. Overall, higher agricultural carbon productivity embodies both economic efficiency and environmental sustainability, driving agriculture's transition toward an ecologically circular model (Huang *et al.*, 2024). Thus, it was proposed that:

H_3: Carbon trading policy stimulates the development of ecological circular agriculture by enhancing agricultural carbon productivity.

Research design

This study considered the implementation of China's carbon emissions trading policy as a quasi-natural experiment to examine the impact of carbon trading policy on the development level of ecological circular agriculture. Using a difference-in-differences (DID) approach, it constructs the following econometric model:

$$ECA_{it} = \alpha_0 + \alpha_1\, did_{it} + \alpha_2\, X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$$did_{it} = Treat_{it} * Post_{it}$$

where i and t denote region and year, respectively. The explained variable ECA_{it} represents the development level of ecological circular agriculture, quantified through a composite index constructed in this study. The variable $Treat_{it}$ is a dummy variable indicating carbon trading pilot regions, and $Post_{it}$ is a time dummy variable. The interaction term did_{it} serves as the core explanatory variable; specifically, $did_{it} = 1$ indicates that province (municipalities) i adopted the carbon trading policy in year t. The coefficient α_1 of did_{it} captures the net effect of carbon trading policy on ecological circular agriculture development. Control variables X_{it} include factors influencing ecological circular agriculture. The model incorporates province fixed effects μ_i and year fixed effects λ_t. The error term ε_{it} accounts for unobserved stochastic factors.

Robustness evaluation

To verify the reliability of the baseline regression results, this study performed a series of robustness tests.

Placebo test. To rule out the influence of unobservable random factors, a placebo test was conducted using 500 randomized simulations. Specifically, eight provinces were randomly selected as a fictional treatment group for the policy year 2013, with the remaining 22 provinces serving as the control group. This procedure was repeated 500 times to generate a distribution of estimated coefficients.

Propensity score matching (PSM-DID). A logit model was used to estimate propensity scores based on relevant covariates to address potential selection bias. This ensured that the treatment and control groups had similar pre-policy characteristics, allowing for a more accurate causal inference.

Alternative group specifications. Two additional checks were conducted: excluding Sichuan and Fujian provinces (which launched markets in 2016) to mitigate temporal heterogeneity and removing regions with high initial development levels (Beijing, Tianjin, Shanghai, and Guangdong) to eliminate potential sample bias.

Heterogeneity analysis

Given the disparities in economic conditions and resource endowments, this study examined the differential impacts of carbon trading policy through three lenses.

Regional heterogeneity. The 30 provinces were categorized into Eastern, Central, and Western regions. An inter-group difference test was performed to identify locational variations in policy efficacy.

Carbon price tiers. Pilot regions were divided into high-price and low-price groups based on the median value of average transaction prices (2013–2021) sourced from the CSMAR (2022).

Agricultural labor productivity. The sample was split into high-productivity and low-productivity groups based on the median ratio of agricultural value added to employment. This assessed whether existing production efficiency influenced the ability of farming entities to adapt to carbon trading incentives.

Variable measurement and description

Explained variable

Ecological circular agriculture (*ECA*) was measured through a composite index structured across four dimensions based on agroecological principles (Altieri *et al*., 2018) and the "3R" framework of the circular economy (Liu *et al*., 2017). This study used the entropy weight method to objectively assign weights to each indicator to quantify provincial *ECA* development levels. Detailed formulae and data sources are provided (Table 1).

Table 1. Measurement system for ecological circular agriculture (ECA) development level.

Dimension	Specific indicator	Attribute
Ecological benefits	Carbon emission intensity per unit area	N
	Fertilizer application intensity	N
	Pesticide application intensity	N
Resource utilization efficiency	Multiple cropping index	P
	Agricultural water use efficiency	P
	Fertilizer use efficiency	P
Technological application level	Proportion of water-saving irrigated area	P
	Agricultural patent intensity	P
Economic sustainability	Green food certification count	P
	Green total factor productivity	P

P: positive indicator, where higher values indicate a higher level of ecological circular agriculture development; N: negative indicator, where lower values represent a higher level of development.

Core explanatory variable

The explanatory variable *did* represents the interaction term between *Post* and *Treat*. According to official guidelines, the initial carbon trading pilot regions established in 2013 included Beijing, Shanghai, Guangdong, Tianjin, Shenzhen, Hubei, and Chongqing. In 2016, Sichuan and Fujian were added to this list. This study categorized the provinces into treatment and control groups based on whether they participated in the pilot program.

To avoid administrative overlap, Shenzhen was excluded from the treatment group, as it is a sub-provincial city within Guangdong Province. As a result, the treatment group consists of eight provinces (municipalities): Beijing, Shanghai, Tianjin, Guangdong, Hubei, Chongqing, Sichuan, and Fujian. The control group includes 22 non-pilot provinces and autonomous regions, with Tibet, Hong Kong, Macao, and Taiwan excluded due to data constraints. Since China's carbon trading market was gradually implemented after 2013, the policy shock year is designated as 2013. Consequently, *did* equals 1 for treatment provinces in 2013 and subsequent years and 0 otherwise, while control provinces retain a *did* value of 0 throughout the study period.

Mediating variables

The mediating variables in this study were ecological technology investment (*ETI*) and agricultural carbon productivity (*ACP*). This study adopts the density of green agricultural innovation patents granted to measure ecological technology investment and the ratio of agricultural added value to agricultural carbon emissions to measure agricultural carbon productivity.

Control variables

To control for the influence of other factors on the research results, the following variables were introduced: Per capita disposable income (*LI*), measured by the ratio of agricultural gross output value to employment in the primary sector, with logarithmic transformation applied; (2) cultivated land area (*TI*), in 10 thousand hectares; (3) rural education level (*RE*), proxied by the average years of schooling among rural residents; (4) industrial structure upgrading (*IU*), measured by the ratio of tertiary sector added value to secondary sector added value, reflecting industrial structure sophistication (Wang *et al*., 2019); (5) forest resource abundance (*FR*), represented by forest coverage rate; and (6) technological progress (*TP*), defined by the number of agricultural green technology patents granted (in thousands).

Data sources and descriptive statistics

This study utilized panel data from 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan), covering the years 2006 to 2021. The data is primarily obtained from several sources, including the China Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Statistical Yearbook, China Energy Statistical Yearbook, China Population and Employment Statistical Yearbook, and statistical yearbooks from provincial or municipal offices. Missing values for specific years were filled in using linear interpolation to ensure data completeness. Additionally, all continuous variables were subjected to 1 % winsorization to minimize the impact of outliers. Descriptive statistics for the variables are summarized (Table 2).

Table 2. Descriptive statistics of the study variables.

Variable	Observations	Mean	Standard deviation	Minimum values	Maximum values
ECA	480	0.164	0.081	0.07	0.71
did	480	0.138	0.345	0	1
ETI	480	0.673	2.478	0	28.54
ACP	480	5.06	2.557	1.709	23.502
LI	480	11.423	0.588	10.097	12.713
TI	480	433.737	318.999	16.06	1586.41
RE	480	7.622	0.646	5.48	9.73
IU	480	1.232	0.674	0.561	4.768
FR	480	0.33	0.185	0.032	0.66
TP	480	0.152	0.245	0	1.627

ECA: ecological circular agriculture index; *did*: difference-in-differences interaction term for *Post* (time) × *Treat* (carbon trading); *ETI*: ecological technology investment (proxied by the density of granted green agricultural innovation patents); *ACP*: agricultural carbon productivity (agricultural added value to agricultural carbon emissions ratio); *LI*: per capita disposable income (log-transformed); *TI:* cultivated land area (10 thousand hectares); *RE*: rural education level (average years of schooling); *IU*: industrial structure upgrading index; *FR*: forest resource abundance (forest coverage rate); *TP*: technological progress (measured by the number (thousands) of granted agricultural green technology patents).

RESULTS AND DISCUSSION

Empirical results

Benchmark regression results

This study used the DID model to evaluate the impact of carbon trading policy on ecological circular agriculture development. The coefficients for the carbon trading policy remained positive and statistically significant across all regression specifications after incrementally incorporating control variables (Table 3). These results are consistent with findings from Wang *et al*. (2023), who argue that carbon trading mechanisms facilitate low-carbon transitions in agricultural practices. This positive effect is attributed to the policy's dual role in balancing cost constraints with incentives, guiding production models toward sustainability, and fostering technological innovation. Specifically, the results indicate that carbon trading policy significantly enhances ecological circular agriculture development levels in pilot provinces (municipalities) by 3.5 %, providing strong validation of H_1.

Table 3. Difference-in-differences (DID) estimates of the impact of carbon trading policy on ecological circular agriculture (ECA).

	ECA						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
did	0.046**	0.042**	0.039**	0.035**	0.036**	0.035**	0.035**
	(0.020)	(0.018)	(0.018)	(0.016)	(0.015)	(0.015)	(0.015)
LI		-0.178	-0.179	-0.112	-0.117	-0.135	-0.115
		(0.116)	(0.112)	(0.106)	(0.105)	(0.102)	(0.093)
TI			-0.001*	-0.001**	-0.001**	-0.001*	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IU				0.040	0.035	0.036	0.040*
				(0.025)	(0.024)	(0.024)	(0.021)
RE					0.029*	0.028*	0.031**
					(0.015)	(0.015)	(0.014)
FR						0.118	0.145*
						(0.079)	(0.075)
TP							0.047**
							(0.019)
Constant	0.158***	2.192	2.243*	1.429	1.265	1.433	1.146
	(0.003)	(1.323)	(1.276)	(1.218)	(1.161)	(1.127)	(1.009)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.884	0.890	0.893	0.898	0.901	0.903	0.909
N	480	480	480	480	480	480	480

(1)–(7) represent regression specifications where control variables are added incrementally to test the robustness of the core coefficient. *ECA*: ecological circular agriculture index; *did*: difference-in-differences interaction term for *Post* (time) × *Treat* (carbon trading); *LI*: per capita disposable income (log-transformed); *TI:* cultivated land area (10 thousand hectares); *RE*: rural education level (average years of schooling); *IU*: industrial structure upgrading index; *FR*: forest resource abundance (forest coverage rate); *TP*: technological progress (measured by the number (thousands) of granted agricultural green technology patents). Year FE and Province FE denote year and province fixed effects, respectively. Values in parentheses are standard errors. *** ** *: 1, 5, 10 % significance.

Pre-treatment parallel trends test

To validate the assumption of parallel trends, this study used the event study approach (Callaway and Sant'Anna, 2020) to plot dynamic treatment effects (Figure 2). Before policy implementation in 2013, the trends in ecological circular agriculture development between pilot and non-pilot regions exhibited no significant divergence. However, after 2013, pilot provinces began to experience a notable upward shift, with the effect becoming more pronounced over time. These results confirm that the assumption of parallel trends is valid, which enhances the credibility of the DID estimates.

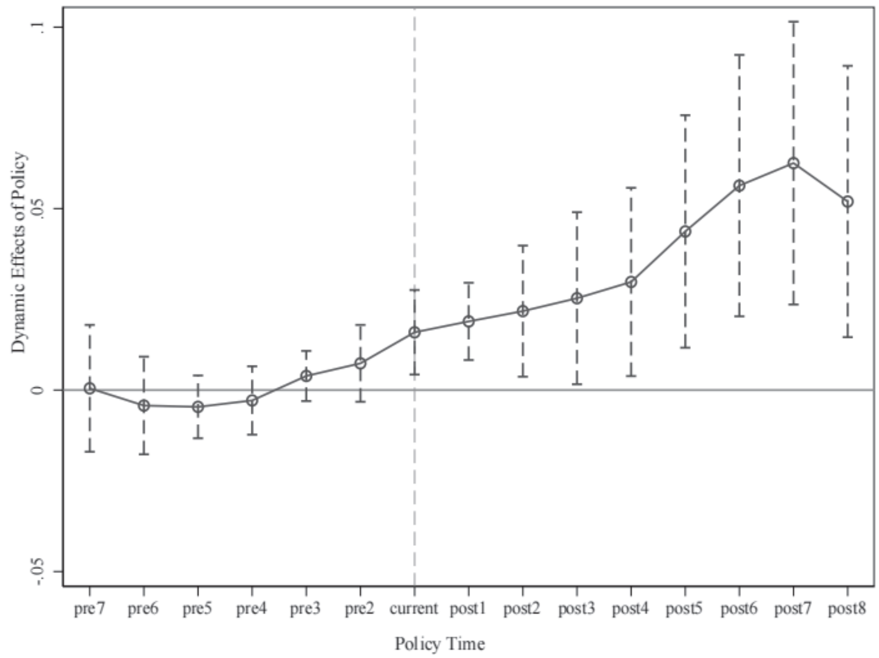

Figure 2. Event study estimates for parallel trends and dynamic treatment effects of carbon trading policy on ecological circular agriculture (ECA). The x-axis represents the time relative to the policy implementation year, which is designated as 2013; "pre" indicates the number of years prior to the policy shock (e.g., pre7 corresponds to 2006); "current" refers to the year of implementation (2013); "post" indicates the number of years following the implementation (e.g., post8 corresponds to 2021).

Placebo test

This study conducted a placebo test to determine whether changes in the development level of ecological circular agriculture are primarily due to the effects of the carbon trading policy rather than other unobservable factors (Figure 3). Specifically, 2013 was designated as the policy implementation year, and 8 out of 30 provinces were randomly selected to form a 'fictional' treatment group, with the remaining 22 provinces serving as the control group; this randomized procedure was then repeated for 500 iterations. The regression coefficients obtained through random sampling followed a normal distribution, with most coefficient values clustered around zero. Moreover, there was a significant deviation from the actual benchmark regression coefficient of 0.035. These findings suggest that based on fictional data, the hypothetical carbon trading policy does not contribute to the development of ecological circular agriculture, effectively ruling out the influence of random factors.

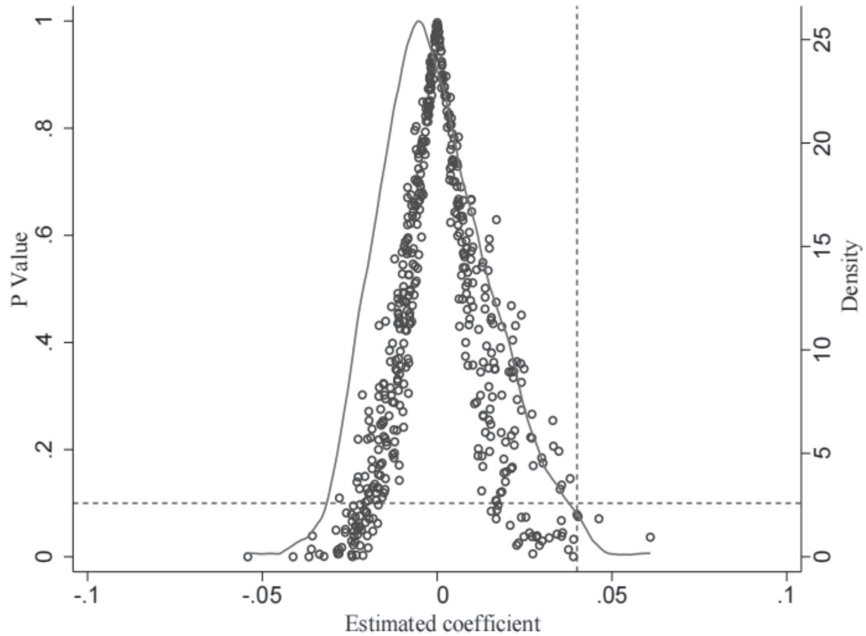

Figure 3. Placebo test based on randomized policy assignment for ecological circular agriculture (ECA).

Robustness evaluation

Propensity score matching-difference-in-differences (PSM-DID) test

To address potential selection bias, the logit model (Ventz *et al.*, 2022) was used to estimate propensity scores for participation in carbon trading policies at the provincial level using covariates. As shown in Column (1) (Table 4), the core coefficient remained positive and significant, confirming the robustness of baseline findings.

Alternative treatment and control groups

Two robustness checks were conducted. First, excluding Sichuan and Fujian provinces (launched carbon markets in 2016) to mitigate heterogeneity (Column (2)); second, removing Beijing, Tianjin, Shanghai, and Guangdong (higher-than-average ecological circular agriculture levels) to eliminate potential bias (Column (3)) (Table 4). In both cases, the carbon trading policy coefficient retained positive significance, reinforcing the robustness of its positive effect on ecological circular agriculture.

Mechanism analysis

Based on the analysis of policy effects, this study further investigates the mechanisms through which carbon trading policy influences the development of ecological circular agriculture. The study focused on two mediating channels: ecological technology

Table 4. Propensity score matching-difference-in-differences (PSM-DID) and alternative specifications for the impact of carbon trading policy on ecological circular agriculture (ECA).

	ECA		
	PSM-DID	Other robustness checks	
	(1)	(2)	(3)
did	0.021***	0.045**	0.017*
	(0.005)	(0.020)	(0.009)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
R^2	0.927	0.908	0.934
N	268	448	416

Controls refers to the same set of control variables used in Table 3, including *LI*, *TI*, *IU*, *RE*, *FR*, and *TP*. Column (1) reports the PSM-DID estimation results; Column (2) reports the results after excluding Sichuan and Fujian provinces; and Column (3) reports the results after excluding Beijing, Tianjin, Shanghai, and Guangdong. Year FE and Province FE denote year and province fixed effects, respectively. Values in parentheses are standard errors. *** ** *: 1, 5, 10 % significance.

investment (*ETI*) and agricultural carbon productivity (*ACP*). To empirically test these mechanisms, the following econometric models were constructed:

$$Media_{it} = \beta_0 + \beta_1\, did_{it} + \beta_2\, X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

$$ECA_{it} = \gamma_0 + \gamma_1\, did_{it} + \gamma_2\, Media_{it} + \gamma_3\, X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $Media_{it}$ represents the mediating variables and γ_2 quantifies the indirect effect of the carbon trading policy through these mechanisms. Other variables are consistent with Equation (1).

The results of the mechanism analysis (Table 5) show that columns (1) and (3) use ecological technology investment and agricultural carbon productivity as dependent variables, respectively, to examine the impact of the carbon trading policy on these mediators. The estimates reveal statistically significant positive coefficients for *did*, indicating that it substantially enhances ecological technology investment and agricultural carbon productivity.

These findings align with prior studies by Feng *et al*. (2024) and Yang *et al*. (2024), which suggest that carbon trading policy encourages agricultural producers to invest in ecological technology research and development and adoption through economic incentives. This study further focuses on the specific field of ecological

Table 5. Mechanism analysis. Effects of carbon trading policy on ecological circular agriculture (ECA) through ecological technology investment (ETI) and agricultural carbon productivity (ACP).

	(1) *ETI*	(2) *ECA*	(3) *ACP*	(4) *ECA*
did	1.123***	0.022***	0.390**	0.030***
	(0.319)	(0.005)	(0.192)	(0.005)
ETI		0.012***		
		(0.002)		
ACP				0.003***
				(0.001)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.737	0.942	0.880	0.930
N	480	480	480	480
Sobel test	0.0114*** (z = 3.592)		0.0064** (z = 2.550)	
Goodman test1	0.0114*** (z = 3.579)		0.0064** (z = 2.535)	
Goodman test2	0.0114*** (z = 3.604)		0.0064** (z = 2.566)	
Indirect effect	0.0114*** (z = 3.592)		0.0064** (z = 2.105)	
Direct effect	0.0222*** (z = 3.823)		0.0225*** (z = 3.715)	
Total effect	0.0336*** (z = 5.200)		0.0290*** (z = 4.469)	
Mediation proportion	0.3391		0.2217	

ECA: ecological circular agriculture index; *did*: difference-in-differences interaction term for *Post* (time) × *Treat* (carbon trading); *ETI*: ecological technology investment (proxied by the density of granted green agricultural innovation patents); *ACP*: agricultural carbon productivity (agricultural added value to agricultural carbon emissions ratio). Controls includes the full set of variables (*LI*, *TI*, *IU*, *RE*, *FR*, and *TP*) consistent with Table 3. Values in parentheses are standard errors. The Sobel and Goodman tests assessed the significance of the mediating effects. *** ** *: 1, 5, 10 % significance.

circular agriculture, clarifies how carbon trading promotes the development of ecological circular agriculture by enhancing investments in ecological technology and increasing agricultural carbon productivity, expands the research scope regarding the relationship between carbon trading policy and agricultural development, and provides more targeted theoretical support for policy-making and practice.

To formally evaluate the mediating effects, the Sobel and Goodman tests were utilized. These tests are particularly effective for calculating the Z-statistics of indirect paths and quantifying the mediation proportion, providing a clear measure of the extent to which the policy's impact is transmitted through specific channels. The results indicate significant mediation: ecological technology investment (*ETI*) accounts for 33.91 % of the total effect, while agricultural carbon productivity (*ACP*) accounts for

22.17 %. These findings validate H_2 and H_3, confirming that the carbon trading policy fosters ecological circular agriculture development through these dual mechanisms. To further ensure the robustness of these mediation pathways, the Bootstrap method was used to estimate confidence intervals. As a non-parametric approach, Bootstrap does not require the indirect effect to follow a normal distribution, offering a more reliable and rigorous statistical confirmation. The results reveal that the 95 % bias-corrected confidence intervals for both *ETI* and *ACP* exclude zero, reinforcing the significance of the identified mediation effects.

Heterogeneity analysis

In examining the carbon trading policy impact on ecological circular agriculture, a single macro-level perspective was found insufficient for policy refinement and implementation. Multifaceted factors, including economic conditions, resource endowments, and policy landscapes, influence the development of ecological circular agriculture. Meanwhile, variables like geographic positioning, carbon pricing mechanisms, and agricultural labor productivity show significant heterogeneity. Studying these variations helped understand how carbon trading policy works in different contexts and overcome the limitations of uniform policies. This analysis provides a scientific basis for governments to develop differentiated strategies, optimize resource allocation, and promote more efficient, equitable, and resilient development of ecological circular agriculture. Therefore, this study conducted three heterogeneity analyses on regional disparities, carbon price, and agricultural productivity.

Regional heterogeneity

Variations in economic conditions, resource availability, and regional policy priorities lead to divergent policy outcomes. Factors such as funding, technology, forest vegetation resources, and supporting infrastructure significantly influence the efficacy of carbon trading policy (Li *et al*., 2024; Liu *et al*., 2023, 2024a). To address this gap, regional heterogeneity was analyzed by categorizing 30 provinces into eastern, central, and western regions (Table 6), and the inter-group difference test was conducted successfully.

The impact of the carbon trading policy on ecological circular agriculture varies across regions due to locational differences. In eastern China, the policy has positively affected ecological circular agriculture thanks to strong economic and technological resources (Dai *et al*., 2025). However, as practices mature, market saturation and diminishing returns on technology investments have slowed growth (Gan *et al*., 2024). In the western region, the carbon trading policy shows strong potential. From 2021 to 2023, it reduced enterprise taxes by over CNY 400 billion through favorable tax policies. By the end of 2023, the balance of green loans in this area increased by 30.1 % (PBC, 2024) compared to the previous year. These measures encourage businesses and farmers to adopt better ecological farming practices and improve their operations. Additionally, the region’s ample land, abundant renewable energy, and other resources offer great opportunities for large-scale ecological farming and breeding.

Table 6. Heterogeneity analysis of carbon trading policy effects on ecological circular agriculture (ECA) across regions, carbon price levels, and agricultural productivity groups.

	ECA						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Eastern	Central	Western	High-price group	Low-price group	High-productivity group	Low-productivity group
did	0.028***	0.006	0.033***			0.031***	0.019***
	(0.011)	(0.009)	(0.005)			(0.010)	(0.004)
DID_{high}				0.033***			
				(0.011)			
DID_{low}					0.021***		
					(0.007)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.908	0.964	0.962	0.904	0.902	0.909	0.958
N	176	128	176	480	480	240	240
p statistic	0.038**	0.074*	0.002***	0.010**		0.044**	

(1)–(7) represent sub-group regressions based on different regional and structural characteristics; (1)–(3) represent the Eastern, Central, and Western regions, respectively; (4)–(5) denote the high-price and low-price tiers of carbon trading pilot regions; (6)–(7) represent the high-productivity and low-productivity groups based on agricultural labor productivity. *did*: difference-in-differences interaction term for *Post* (time) × *Treat* (carbon trading); DID_{high}: the interaction term (*Post* × *Treat*) for the subgroup of pilot regions with average carbon trading prices above the sample median (including Beijing, Shanghai, Guangdong, Chongqing, and Fujian); DID_{low}: the interaction term for pilot regions with average carbon trading prices below the median (including Tianjin, Hubei, and Sichuan). Controls includes the full set of variables (*LI*, *TI*, *IU*, *RE*, *FR*, and *TP*) consistent with Table 3. Values in parentheses are standard errors. The Sobel and Goodman tests assess the significance of the mediating effects. *** ** *: 1, 5, 10 % significance.

Overall, the combined advantages make the policy impact slightly stronger in the West than in the East. However, structural and institutional barriers constrain the effectiveness of carbon trading policies in the central region. As a traditional agricultural heartland, its long-standing focus on yield stability has led to a path dependence on conventional practices, hindering the adoption of eco-friendly technologies and reducing farmers' participation (Wang *et al*., 2022). Meanwhile, the expansion of energy-intensive agri-industries such as food processing and feed production, coupled with limited profits, weakens incentives for technological upgrading (Du *et al*., 2023). Moreover, local governments' emphasis on industrial and grain output, along with weak coordination between low-carbon and agricultural policies, further limits policy effectiveness.

Heterogeneity in carbon allowance trading prices

Since pilot regions hold substantial autonomy in operating their carbon trading markets, the enforcement intensity of policies varies significantly across different pilot areas. Eight pilot regions were classified into distinct tiers based on their 2006–2021 average transaction prices, sourced from the China Stock Market and Accounting Research database (CSMAR, 2022). This study conducts separate regression analyses for high-price and low-price groups to examine the differential impacts of carbon trading prices on ecological circular agriculture. The high-price group includes Beijing, Shanghai, Guangdong, Chongqing, and Fujian, while the low-price group includes Tianjin, Hubei, and Sichuan.

The carbon trading policy exhibits significant positive effects on ecological circular agriculture across all carbon price levels (Table 6), though the magnitude of impact varies substantially with price tiers. Regions with higher carbon prices demonstrate a more substantial policy effect than low-price regions. This disparity arises because entities in high-price regions face elevated decarbonization costs, incentivizing them to actively adopt low-carbon technologies and ecological circular agriculture practices to reduce compliance expenses and capitalize on carbon credit revenues. Such price-driven incentives accelerate technological upgrading and systemic shifts toward circular agroecosystems, enhancing agricultural sustainability. In contrast, low-price regions experience weaker motivation for transformation: agricultural producers may perceive the costs of maintaining traditional practices as lower than transitioning to ecological circular agriculture, resulting in limited investments in sustainable technologies.

Heterogeneity in agricultural labor productivity

Agricultural labor productivity is a crucial metric for assessing production efficiency and shows significant disparities across different regions and farming entities. In this study, agricultural labor productivity is measured as the ratio of agricultural value added to agricultural employment. The sample was classified into high-productivity and low-productivity groups based on the median value.

The results of the heterogeneity test for different productivity levels (Table 6) reveal that the high-productivity group experienced a significantly greater improvement in ecological circular agriculture after the policy was implemented compared to the low-productivity group. This difference can be attributed to the fact that high-productivity regions typically have access to advanced production technologies, better management practices, and a more skilled labor force. These advantages allow them to quickly take advantage of new opportunities under the carbon trading policy. On the other hand, low-productivity regions face challenges due to outdated technologies, inefficient resource management, and limited technical training, which hinder their ability to fully benefit from policy incentives. The weaker response to the policy in these areas highlights the need for targeted interventions, such as precision agronomy extension services and AI-driven decision-support tools, to help bridge productivity gaps and enhance sustainability outcomes.

CONCLUSIONS

This study demonstrates that carbon trading policy significantly promotes ecological circular agriculture in China, increasing the development level of pilot regions by 3.5 %. This effect is mainly transmitted through ecological technology investment (33.91 % of the total effect) and agricultural carbon productivity (22.17 %). Policy impacts are stronger in the Eastern region, where institutional support and market maturity are higher, as well as in areas with higher carbon prices and agricultural labor productivity. These findings indicate that market-based carbon trading can align ecological sustainability with agricultural modernization through innovation and efficiency improvements.

Several policy implications emerge from these findings. First, carbon trading coverage and standardized agricultural carbon accounting should be expanded to encourage broader farmer participation through simplified registration and government-led certification programs. Second, given that technology investment and productivity are the main transmission channels, dedicated funding and fiscal incentives should support low-carbon technologies such as biochar and precision irrigation, particularly for smallholders.

Regional disparities should also be addressed through tailored interventions, including agricultural digitalization in central regions and the expansion of demonstration zones in developed areas. In addition, establishing a unified national carbon trading platform would improve market liquidity, reduce regional price disparities, and strengthen long-term incentives for ecological circular agriculture. These findings provide empirical support for both China's carbon trading policy and broader policy adaptation.

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