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Evaluating the Effects of the 'Pilot Zone' Policy on China's Agricultural Green Development

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Abstract: Green agriculture is a new sustainable agricultural development model that coordinates agricultural development with the environment which has been vigorously promoted in China in recent years. With the support of national policies, China has set up 130 pilot zones for green agricultural development. Taking these pilot zones as quasi-natural experimental areas, the difference-in-differences (DID) method and agricultural green total factor productivity are used to evaluate the effect of the policy in the pilot zones. The findings indicate that the pilot zones notably diminish non-point source agricultural pollution without affecting agricultural added value and improve agricultural green total factor productivity by improving technical efficiency. Heterogeneity analysis shows that the effectiveness of this policy varies regionally. The eastern region of China, the main agricultural producing areas, and the regions with higher initial environmental pollution levels and abundant educational resources experience more pronounced benefits. Based on the regional characteristics of different regions, this study considers the factors such as agricultural resource endowment and development basis and explores how the policy effects of agricultural green development in different regions, which has certain guiding significance for the continuous improvement in China's agricultural green development policies.

Keywords: green development; agriculture; total factor productivity; difference-in-differences (DID) method

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1. Introduction

As a cornerstone of societal advancement, agriculture has the dual attributes of ecology and economy; the intersection of agricultural economic development with resource and environmental concerns has garnered extensive attention from scholars and policymakers globally [1,2]. Under the dual challenges of food security crises and environmental costs, China, as the country with the largest food supply in the world, urgently needs to shift its extensive agricultural development mode to a sustainable and green development mode [3,4]. Rodale (1983) articulated that agricultural practices should foster a sustainable cycle with the environment, thereby introducing the concept of sustainable agriculture [5]. Expanding on this by defining sustainable agriculture as an integration of environmental stewardship, food sufficiency, and social equity, Ulbricht (1985) developed a preliminary set of indicators to measure the sustainability of agricultural systems based on sustainability principles and methodologies [6]. Subsequently, the United States, the Food and Agriculture Organization of the United Nations, and the World Sustainable Agriculture Association further promoted the formation and development of sustainable agriculture. Researchers

in different countries have conducted detailed analyses of the impact factors and the effectiveness of policies on sustainable agriculture [3,7–11].

At present, China's agriculture is mostly small-scale and scattered cultivation; the main problems include insufficient levels of agricultural mechanization [12,13], excessive reliance on fertilizer inputs, environmental deterioration [14], and so on. The regional imbalance of economic development, production technology, and education level cause the green development of agriculture to face different difficulties in different regions of China [4,15,16]. Therefore, how to comprehensively improve the efficiency of agricultural development and achieve the green development of agriculture throughout the country is a long-term and important problem in China [3,10,17]. In order to solve this problem, the Ministry of Agriculture and Rural Affairs of China, alongside seven other departments, initiated the creation of agricultural green development pilot zones in three phases during 2017, 2019, and 2022; a total of 130 zones have been established. Although these regions have different regional characteristics, agricultural resource endowments, and development bases, quantifying the effects of agricultural green development policies in different regions and identifying possible influencing factors have important reference value for the research of agricultural green development policies in China.

2. Methods and Data

2.1. Difference-in-Differences (DID) Method

The DID method is widely used to identify policy effects [18]. It regards the implementation of a certain policy as a natural experiment. By adding a control group that is not affected by the policy to the sample and comparing it with the experimental group of sample points that are originally affected by the policy, the net impact of policy implementation on the object of analysis is investigated [18,19]. In this study, the implementation of agricultural green development pilot zones, considered an exogenous policy intervention, is treated as a quasi-natural experiment. The DID method is employed for causal identification, specifically to assess the impact of the establishment of pilot zones on agricultural green total factor productivity at the city level. This approach allows us to determine whether the policy significantly influences the green development of urban agriculture. Cities that have implemented the agricultural green development pilot zones are designated as the treatment group, while those without such initiatives serve as the control group. The year each pilot zone was established marks the treatment event, and the period of analysis is divided into a pre-treatment phase (2010–2016) and a post-treatment phase (2017–2019). The baseline model equation is structured as follows:

$$TFP_{it} = \alpha + \beta_1 Treat_i \times Post_t + \beta_2 X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

where TFP_{it} represents the agricultural green total factor productivity of each city in the sample; $Treat_i$ is an indicator variable of whether city i is in the treatment group, that is, whether the city has carried out the construction of an agricultural green development pilot zone. If the prefecture-level city has carried out the construction of an agricultural green development pilot zone within the sample time interval, it is assigned a value of 1; otherwise, it is assigned a value of 0. $Post_t$ indicates whether the policy has been implemented or not. $Post_t = 1$ represents the time after implementation, while Post(t) = 0 is the time before implementation. $\text{Treat}_i \times \text{Post}_t$ is a dummy variable which is equal to 1 if city i belongs to the treatment group and time t is after the start of the policy. X_{it} represents the time-varying economic and social characteristics of each city. γ_i represents the city-fixed effects to control for the time-invariant characteristics of each city. δ_t represents the time-fixed effects to control for time trends. ε_{it} represents the idiosyncratic error term. Under this model specification, the coefficient β_1 of the interaction term $Treat_i \times Post_t$ is the magnitude of the net effect of the agricultural green development pilot zones, which is the focus of this paper.

2.2. Agricultural Green Total Factor Productivity (TFP)

Total factor productivity is widely used to measure the level and efficiency of green development [9,20–23]; researchers have carried out in-depth analyses on the influencing mechanism and driving factors of agricultural green total factor productivity in China [9,20], but the impact of total factor productivity on green pilot areas is not very clear. This paper uses agricultural green TFP to measure each city's agricultural green development level. A higher value indicates higher agricultural green TFP, a higher quality of agricultural economic growth, and a higher level of agricultural green development in that city [18,24]. The Malmquist total factor productivity index (MI), technical efficiency change (EC), and technological change (TC) are used to interpret TFP, and their formulas are as follows [14]:

$$MI^t(t-1,t) = \frac{Score_t(x_t, y_t)}{Score_t(x_{t-1}, y_{t-1})} \tag{2}$$

where $Score_t(x_t, y_t)$ and $Score_t(x_{t-1}, y_{t-1})$ represent the data envelopment analysis (DEA) efficiency scores of (x_t, y_t) and (x_{t-1}, y_{t-1}), respectively, with reference to the frontier in period t.

Furthermore, MI could be dichotomized as EC and TC:

$$MI(t-1,t) = EC(t-1,t) \times TC(t-1,t) \tag{3}$$

where $EC(t-1,t) = \frac{Score_t(x_t,y_t)}{Score_{t-1}(x_{t-1},y_{t-1})}$ and $TC(t-1,t) = \sqrt{\frac{Score_{t-1}(x_{t-1},y_{t-1})}{Score_t(x_{t-1},y_{t-1})} \times \frac{Score_{t-1}(x_t,y_t)}{Score_t(x_t,y_t)}}$.

In calculating agricultural green TFP using the MI method, the input indicators encompass total cultivated land resources, agricultural labor force, and agricultural electricity consumption. The year-end total area of cultivated land gauges the total cultivated land resources. The agricultural labor force is determined by the number of individuals employed in agriculture, forestry, animal husbandry, and fisheries. Agricultural electricity consumption is collated at the county level and aggregated at the city level. The output indicators consist of desirable and undesirable outputs; the former is assessed through agricultural added value, while the latter is gauged by agricultural non-point source pollution derived from the use of agricultural chemical fertilizers and plastic films.

$Treat_i \times Post_t$ is the interaction term, which represents whether the agricultural green development pilot zone has been established and whether the policy has been enacted. This term is assigned a value of 1 if the city has implemented the pilot zone construction, and 0 otherwise.

The control variables considered in this study focus on the effects of agricultural green development pilot zone construction on agricultural green TFP. Drawing from the existing literature and available city-level data, the selected control variables include per capita GDP (pgdp), the proportion of output from the tertiary industry (third), the city's total annual education expenditure (educ), the total urban population at year-end (urbanization), and the number of students enrolled in secondary vocational and technical schools (student).

2.3. Source of Data

This study treats the establishment of agricultural green development pilot zones as an exogenous shock and investigates its influence on agricultural green TFP. It employs balanced panel data from prefecture-level cities across China from 2010 to 2019. For the input–output indicators required to calculate TFP, data on total cultivated land resources and employment in agriculture, forestry, animal husbandry, and fisheries were sourced from city statistical yearbooks (https://data.cnki.net/yearBook/single?id=N2021050059, accessed on 3 January 2024). Agricultural electricity consumption data were retrieved from the CSMAR database (https://data.csmar.com/, accessed on 19 January 2024), while information on agricultural added value and agricultural non-point source pollution were obtained from the CEIC regional comparison database (https://ceidata.cei.cn/db/, accessed on 31 January 2024). Additionally, data for all control variables and the number of

secondary vocational schools used in the heterogeneity analysis were derived from city statistical yearbooks (https://data.cnki.net/yearBook/single?id=N2021050059, accessed on 3 January 2024).

3. Results

3.1. Descriptive Statistics

Table 1 provides the descriptive statistics for the key variables employed in the analytical model of this paper. The statistics indicate that the average TFP under constant returns to scale (TFP_CRS), which is the main dependent variable in the benchmark regression, stands at 1.134. This variable shows a range from a minimum of 0.002 to a maximum of 14.092. In contrast, for the robustness test, where TFP under variable returns to scale (TFP_VRS) is used as the dependent variable, the mean is slightly higher at 1.179, with values ranging from a minimum of 0.004 to a maximum of 102.492.

Table 1. Descriptive statistics of main variables.

Variable	Interpretation of Variables	Sample Size	Mean	Minimum	Median	Maximum
TFP_CRS	Agricultural Green TFP	2394	1.134	0.002	1.05	14.092
TFP_VRS	Agricultural Green TFP	2394	1.179	0.004	1.042	102.492
pgdp	City-Level Per Capita GDP	2394	0.509	0.065	0.417	2.905
third	Proportion of Tertiary Industry Output	2394	0.409	0.144	0.402	0.792
educ	Total Annual Education Expenditure	2394	6.098	0.2	4.971	52.397
urbanization	Year-End Urban Population	2394	0.515	0.051	0.342	6.493
student	Number of Students Enrolled in Secondary Vocational and Technical Schools	2394	0.485	0.001	0.361	3.304

Table 2 reports the characteristics of agricultural green TFP under constant returns to scale and variable returns to scale. The data in the table are the means of the corresponding variables of each city in the sample for each year.

Table 2. Trends in agricultural green total factor productivity.

Year	Constant Returns to Scale			Variable Returns to Scale		
	MI	EC	TC	MI	EC	TC
2011	0.830	0.008	0.935	0.809	0.009	0.806
2012	1.149	0.084	0.001	1.104	1.269	0.014
2013	1.095	0.078	1.456	1.092	0.092	1.181
2014	1.048	0.083	1.398	1.105	0.103	1.071
2015	1.063	0.148	0.691	1.018	0.136	0.748
2016	1.107	0.076	1.286	0.991	0.079	1.255
2017	1.103	0.031	3.087	0.957	0.051	1.888
2018	1.162	0.110	1.086	1.080	0.101	1.068
2019	1.222	0.095	1.213	1.086	0.083	1.310

The data presented in Table 2 illustrate the temporal trends in the agricultural green total factor productivity MI, along with its components EC and TC, under two different scenarios. Overall, there is some fluctuation in these variables as the years progress, yet the trends under constant returns to scale and variable returns to scale remain relatively consistent. Consequently, this study also employs the agricultural green TFP calculated under variable returns to scale as a substitute for that under constant returns to scale in the robustness test. This substitution aims to further validate the robustness of results.

3.2. Regression Results of Benchmark Model

The impact of the implementation of agricultural green development pilot zones on agricultural green TFP is analyzed using a DID method with two-way fixed effects. The

regression outcomes from the benchmark model are detailed in Table 3, where all results are statistically significant at the 1% level using double-tailed tests. The columns (1) to (5) of the table show the results from estimations that control for control variables and incorporate two-way fixed effects.

Table 3. Regression results of benchmark model.

Variable	(1)	(2)	(3)	(4)	(5)
	Agricultural Non-Point Source Pollution	Agricultural Added Value	TFP	EC	TC
Treat × Post	−1.962 **	5.525 ***	2.133 ***	10.004 **	0.048
	(1.07)	(2.00)	(0.07)	(8.49)	(0.28)
pgdp	3.953 ***	−0.837	−0.151	−9.057	0.190
	(1.43)	(4.52)	(0.15)	(14.71)	(0.63)
third	−12.337 *	−13.223	−1.487 ***	−2.434	4.995 ***
	(7.58)	(14.09)	(0.48)	(4.84)	(1.97)
educ	2.370 ***	0.201	0.007	7.160 ***	−0.073 *
	(0.16)	(0.30)	(0.01)	(0.98)	(0.04)
urbanization	−0.648	−0.334	0.033	−29.892 ***	−1.023 ***
	(1.32)	(2.45)	(0.08)	(7.99)	(0.34)
student	4.501 ***	−1.618	0.058	14.766	1.189 ***
	(1.72)	(3.20)	(0.11)	(10.43)	(0.45)
_cons	−0.57 ***	4.306	0.200	2.416 ***	8.996 ***
	(1.78)	(4.50)	(2.47)	(2.16)	(10.44)
city-fixed effects	controlled	controlled	controlled	controlled	controlled
year-fixed effects	controlled	controlled	controlled	controlled	controlled
N	2394	2394	2394	2394	2394
F	2967.912	2.126	145.928	48.262	94.453
R^2	0.966	0.117	0.378	0.173	0.239

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Clustered standard errors are in parentheses. _cons is the abbreviation for constant.

The estimation results presented in column (3) reveal that when the explained variable is agricultural green total factor productivity, the interaction term treat × post is significantly positive at the 1% level. This result indicates that following the implementation of agricultural green development pilot zones, agricultural green TFP has significantly increased, indicating that policies have a significant promoting effect on agricultural green TPF. When further breaking down green TFP into EC and TC, the results in column (4) show that the interaction term is significantly positive at the 5% level, indicating a significant improvement in EC in the cities implementing the pilot zones. However, the interaction term in column (5) does not reach significance at the 10% level, suggesting no significant impact on TC. This implies that the agricultural green development pilot zone notably enhances EC in cities but does not affect their TC. Columns (1) and (2) show the effects on agricultural non-point source pollution and agricultural added values, or the undesirable and desirable outputs of green TFP. Accordingly, the interaction item in column (1) is negatively significant at the 5% level, and the interaction item in column (2) is positively significant at the 1% level. This result shows that implementing agricultural green development pilot zones can effectively promote the desirable output while significantly reducing the undesirable output, further promoting green TFP.

3.3. Robustness Tests

3.3.1. Expected Effect Test

Although this study employs a DID method with two-way fixed effects to address certain endogeneity issues, this approach primarily guarantees the validity of the results' estimation and inference. However, the presence of other concurrent policies during the study period or the exclusion of specific time-varying characteristics of cities could still potentially bias the benchmark results. To address this issue, an expected effect test, also

known as a temporal placebo test, was performed where the policy implementation year was hypothetically set to 2015 and 2016 (the year of policy implementation) to investigate whether other policies might have influenced the validity of the research results. Outcomes of the expected effect test are presented in Table 4, where Panel A displays the results with the policy year set to 2015, while Panel B details the outcomes for 2016. The results show that the coefficients of Treat_2015 and Treat_2016 in all regression models are statistically insignificant at the 10% level, indicating that advancing policy implementation by one or two years does not significantly alter the measures of agricultural green TFP and its components. These non-significant results suggest that the benchmark results of this paper are attributable to the introduction of agricultural green development pilot zones rather than being influenced by other potential concurrent policies, thereby confirming the robustness of the original results.

Table 4. Results of expected effect test.

	(1)	(2)	(3)	(4)	(5)
Panel A: Hypothetical Policy Implementation in 2015					
	Agricultural Non-Point Source Pollution	Agricultural Green Development	TFP	EC	TC
Treat_2015	−3.005	0.925	0.060	−3.392	0.026
	(4.24)	(2.34)	(0.09)	(4.78)	(0.06)
pgdp	33.147 ***	−0.913	−0.371 **	10.199	0.037
	(2.42)	(4.56)	(0.18)	(9.30)	(0.11)
third	−19.802 ***	−20.493	−0.957 *	−14.946	−0.019
	(7.64)	(14.41)	(0.58)	(29.37)	(0.34)
educ	2.362 ***	0.200	0.007	2.186 ***	−0.003
	(0.16)	(0.31)	(0.01)	(0.62)	(0.01)
urbanization	0.416	0.469	0.012	2.424	0.015
	(1.33)	(2.52)	(0.10)	(5.13)	(0.06)
student	3.093 *	−2.096	0.139	−5.875	−0.068
	(1.73)	(3.26)	(0.13)	(6.64)	(0.08)
_cons	99.374 ***	8.797	1.592 ***	7.697	2.127 ***
	(3.85)	(7.26)	(0.29)	(14.80)	(0.17)
N	2394	2394	2394	2394	2394
F	117.438	0.617	1.252	4.869	0.210
R^2	0.967	0.116	0.134	0.675	0.978
Panel B: Hypothetical Policy Implementation in 2016					
Treat_2016	−3.107	0.738	0.060	−4.339	0.033
	(3.24)	(2.34)	(0.09)	(4.78)	(0.06)
pgdp	33.129 ***	−0.910	−0.371 **	10.163	0.037
	(2.42)	(4.56)	(0.18)	(9.30)	(0.11)
third	−19.796 ***	−20.494	−0.957 *	−14.938	−0.019
	(7.64)	(14.41)	(0.58)	(29.39)	(0.34)
educ	2.363 ***	0.200	0.007	2.188 ***	−0.003
	(0.16)	(0.31)	(0.01)	(0.62)	(0.01)
urbanization	0.408	0.483	0.012	2.265	0.014
	(1.33)	(2.52)	(0.10)	(5.13)	(0.06)
student	3.105 *	−2.098	0.139	−5.848	−0.068
	(1.73)	(3.26)	(0.13)	(6.64)	(0.08)
_cons	99.339 ***	8.813	1.593 ***	7.513	2.128 ***
	(3.85)	(7.26)	(0.29)	(14.80)	(0.17)
city-fixed effects	controlled	controlled	controlled	controlled	controlled
year-fixed effects	controlled	controlled	controlled	controlled	controlled
N	2394	2394	2394	2394	2394
F	117.528	0.608	1.251	4.585	0.234
R^2	0.967	0.116	0.134	0.675	0.978

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Clustered standard errors are in parentheses. _cons is the abbreviation for constant.

3.3.2. Parallel Trend Test

This paper utilizes the DID method to estimate the impact of agricultural green development pilot zones on city agricultural green TFP. However, the effectiveness of the DID method hinges on fulfilling the "parallel trend assumption," which is crucial for ensuring that the estimators derived from the model are consistent. Specifically, this assumption requires that, prior to the implementation of the agricultural green development pilot zones, the cities designated for pilot zone construction and those not designated should exhibit identical trends in agricultural green TFP. Essentially, this means that the trajectory of agricultural green TFP should be unrelated to the anticipated implementation of pilot zones if no such implementation were to take place. To ascertain whether this critical "ad hoc parallel trend assumption" is met, the following test model is proposed:

$$TFP_{it} = \alpha + \sum_{n=-6}^{-2} \theta_n I_t\{t - 2017 = n\} \times Treat_i + \sum_{n=0}^{2} \psi_n I_t\{t - 2017 = n\} \times Treat_i + \beta_2 X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (4)$$

when $t - 2017 = n$, then $I_t\{t - 2017 = n\} = 1$; otherwise, $I_t\{t - 2017 = n\} = 0$. θ_n and ψ_n are the coefficients of the main reasons for testing the "parallel trend assumption". If θ_n is insignificant, it indicates that the "parallel trend assumption" holds.

Figure 1 presents the outcomes of the parallel trend test. (a), (b) and (c) illustrate the regression results for agricultural green TFP, technical efficiency change, and production technology change, respectively. The coefficients prior to policy implementation across these tests are statistically insignificant, indicating no significant divergence in the ad hoc trends between cities in the treatment group and those in the control group. This consistency strongly supports the fulfillment of the "parallel trend assumption". Furthermore, the significant coefficients labeled as After1 and After2 in the first two graphs demonstrate notable differences in the post-policy implementation period between the treatment and control group cities. These results align with the benchmark regression results discussed in earlier sections of this paper, reinforcing the causal impact attributed to policy implementation on the observed variables.

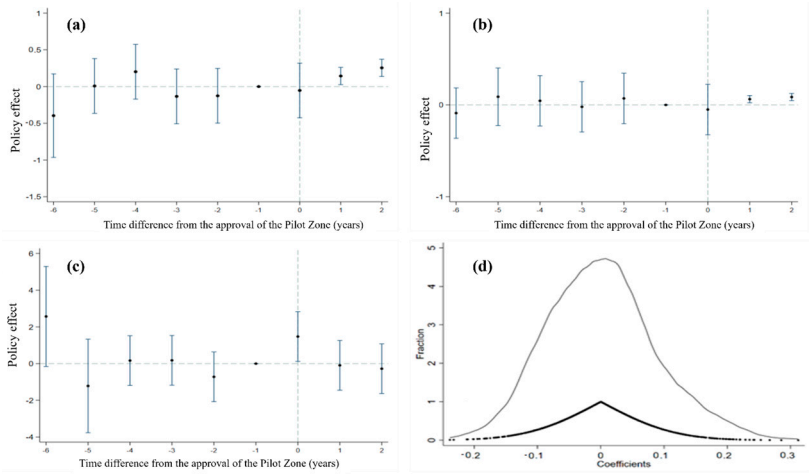


Figure 1. Parallel trend test and placebo test results. (**a**–**d**) illustrate the regression results for agricultural green TFP, technical efficiency change, production technology change, and the outcomes of the placebo test, respectively.

3.3.3. Placebo Test

To mitigate the potential confounding effects of other related policies or time-varying characteristics at the city level during the study period, this subsection conducts a robustness check using a placebo test. The method for the placebo test is as follows: An equivalent number of cities to those in the treatment group is randomly selected from the entire sample of cities. The benchmark model of this study is then re-estimated using this newly formed

sample. This procedure is repeated 1000 times, with the estimated treatment effect from each randomly generated sample being recorded. Subsequently, the proportion of cases in which the absolute value of the treatment effect from the random allocations exceeds the absolute value of the treatment effect observed in the benchmark model is calculated. This proportion is then analyzed to assess its approximation to zero.

Figure 1d depicts the outcomes of the placebo test. This graph illustrates the distribution of coefficients derived from estimating the benchmark regression equation across 1000 random allocations of the treatment group. The treatment effects post-random allocation are predominantly normally distributed, primarily ranging between −0.2 and 0.2, which is significantly lower than the actual treatment effect obtained from the benchmark regression. Notably, the proportion of cases where the absolute value of the treatment effect from the random allocations exceeds the absolute value of the actual treatment effect is zero. Therefore, it can be concluded that the benchmark results withstand the placebo test, effectively ruling out the impacts of other concurrent policies and affirming the robustness of the results.

3.3.4. Propensity Score Matching–Difference-in-Differences (PSM-DID)

In the benchmark regression section of this paper, the DID method was employed to investigate the impact of the agricultural green development pilot zones on the agricultural green TFP of cities, yielding relatively reliable results. However, the comparability of the treatment and control group city samples was not fully addressed in this section. There may be inherent differences in the characteristics of cities within the treatment and control groups prior to policy implementation, which could compromise their comparability. To address potential discrepancies stemming from characteristic differences between the treatment and control group samples, this paper employs the propensity score matching–difference-in-differences (PSM-DID) method. This approach involves matching the treatment group samples with the control group samples based on propensity scores to ensure that the characteristics of the city samples in both groups are more similar and comparable. This matching is intended to produce more accurate estimates of the treatment effects.

For the matching, we utilize city characteristics from the year prior to policy implementation, namely 2016, and employ kernel matching as the technique. The effects of propensity score matching are detailed in Table 5 and Figure 2. According to Table 6, the estimation of propensity scores using the Logit model shows that the coefficients for all variables are significant at the 1% level. There is a notable disparity in the mean values of each variable between the treatment and control group samples prior to matching; this disparity is substantially reduced post-matching, as evidenced by the small t-values, indicating an effective matching process. After matching, there are no significant differences between the treatment and control groups for each variable. Furthermore, Figure 2 illustrates that the treatment and control group samples fall within a common value range and are distributed relatively symmetrically, further affirming the efficacy of propensity score matching.

Table 5. Propensity score matching effect.

Covariance	Logit	Unmatched/Matched	Mean		Bias	Reduced Bias%	*t*-Test	
			Treated	Control			t	*p*-value
pgdp	−1.701 ***	U	0.456	0.516	−20.3		pgdp	−1.701 ***
	0.31	M	0.449	0.443	2	90.3		0.31
third	−2.803 ***	U	0.395	0.411	−17.4		third	−2.803 ***
	(0.81)	M	0.393	0.392	0.9	95		(0.81)
educ	0.071 ***	U	6.416	6.053	7.7		educ	0.071 ***
	(0.02)	M	6.094	5.818	5.9	23.9		(0.02)
urbanization	0.917 ***	U	0.579	0.506	10.4		urbanization	0.917 ***
	(0.18)	M	0.488	0.463	3.6	65.5		(0.18)
student	−0.271 ***	U	0.444	0.490	−10.7		student	−0.271 ***

Note: *** indicates significance at the 1% level. Clustered standard errors are in parentheses.

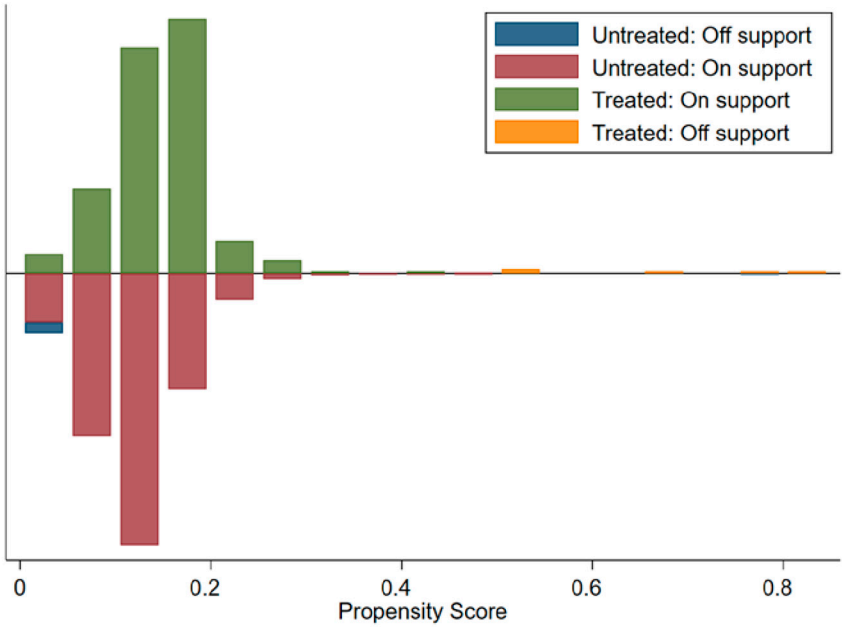


Figure 2. Propensity score matching effect.

Table 6. Propensity score matching–difference-in-differences results (PSM-DID).

Variable	(1)	(2)	(3)	(4)	(5)
	Agricultural Non-Point Source Pollution	Agricultural Added Values	TFP	EC	TC
Treat × Post	−0.161 **	1.094 **	0.509 ***	26.231 ***	2.688 ***
	(0.08)	(0.34)	(0.04)	(5.10)	(0.18)
pgdp	68.226 ***	−0.747	−0.526 ***	−14.254	3.528 ***
	(2.27)	(2.72)	(0.17)	(21.77)	(0.77)
third	28.006 ***	−3.517	−1.746 ***	−47.415	16.528 ***
	(5.68)	(6.81)	(0.43)	(54.48)	(1.94)
educ	1.680 ***	0.055	0.019 *	10.196 ***	−0.258 ***
	(0.14)	(0.17)	(0.01)	(1.36)	(0.05)
urbanization	−1.974 *	0.218	0.209 ***	−31.904 ***	−1.372 ***
	(1.05)	(1.26)	(0.08)	(10.09)	(0.36)
student	−2.494	−0.627	−0.076	14.551	1.313 **
	(1.62)	(1.94)	(0.12)	(15.52)	(0.55)
_cons	−15.648 ***	2.918	19.371	32.486 ***	47.929 ***
	(5.44)	(2.54)	(25.70)	(9.05)	(114.46)
city-fixed effects	controlled	controlled	controlled	controlled	controlled
year-fixed effects	controlled	controlled	controlled	controlled	controlled
N	2353	2353	2353	2353	2353
F	5516.164	0.512	28.852	49.811	155.863
R2	0.977	0.158	0.156	0.178	0.352

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Clustered standard errors are in parentheses. _cons is the abbreviation for constant.

After propensity score matching and teasing out non-paired samples, regressions based on the paired samples using the DID model were conducted. As the results from PSM-DID report in Table 6, the coefficients of treat × post and agricultural non-point source pollution, agricultural added values, TFP, EC, and TC are significant at 5%, 5%, 1%, 1%, and 1%, respectively. This means that the implementation of agricultural green development pilot zones significantly promotes city agricultural TFP, technical efficiency change, production technological change, and agricultural added values; it also significantly reduces agricultural non-point source pollution. In high alignment with the benchmark model results, these results provide further evidence of the robustness of the previous results.

3.3.5. Other Robustness Tests

In addition to parallel trend tests, placebo tests, and propensity score matching–difference-in-differences, this paper conducts further robustness tests to examine the effect of agricultural green development pilot zones on agricultural green TFP, with the results shown in Table 7. Specifically, when we replace agricultural green TFP under constant returns to scale with variable returns to scale, the direction and significance level of the interaction term treat × post remain unchanged. Column (4) presents the estimation result of the logarithmic transformation of the dependent variable agricultural green TFP; the coefficient remains statistically significant at the 1% level, corroborating the benchmark results. Given that the agricultural green TFP among cities within the same province might be correlated due to provincial-level influences, it is prudent to cluster the standard errors at the provincial level to mitigate bias. The results in column (5), which applies this clustering, demonstrate that the key coefficient retains its significance at the 1% level. This suggests that even after accounting for potential correlations among cities within provinces, the benchmark results are robust.

Table 7. Results of other robustness tests.

Variable	(1)	(2)	(3)	(4)	(5)
	TFP_vrs	**EC_vrs**	**TC_vrs**	**lnTFP**	**TFP**
Treat × Post	1.988 ***	2.952 ***	−0.025	0.788 ***	2.133 ***
	(0.23)	(0.93)	(0.25)	(0.04)	(0.41)
pgdp	−0.438	−2.910	0.190	0.051	−0.151
	(0.52)	(2.10)	(0.57)	(0.08)	(0.17)
third	−0.555	1.158	12.275 ***	−0.577 **	−1.487 **
	(1.61)	(6.54)	(1.79)	(0.26)	(0.58)
educ	0.032	0.823 ***	−0.097 **	−0.005	0.007
	(0.03)	(0.14)	(0.04)	(0.01)	(0.01)
urbanization	−0.059	−3.119 ***	−0.761 **	0.042	0.033
	(0.28)	(1.14)	(0.31)	(0.04)	(0.15)
student	−0.058	3.770 **	1.452 ***	−0.054	0.058
	(0.37)	(1.49)	(0.41)	(0.06)	(0.09)
_cons	71.094	2731.591 ***	1165.384 ***	−28.327 **	0.200
	(86.27)	(349.64)	(95.72)	(13.69)	(27.53)
city-fixed effects	controlled	controlled	controlled	controlled	controlled
year-fixed effects	controlled	controlled	controlled	controlled	controlled
N	2394	2394	2394	2394	2394
F	11.004	41.975	93.303	76.698	4.151
R^2	0.155	0.163	0.240	0.226	0.378

Note: *** and ** indicate significance at the 1% and 5%. Clustered standard errors are in parentheses. _cons is the abbreviation for constant.

4. Discussion

The impact of agricultural green development pilot zones on agricultural green TFP may exhibit heterogeneity due to the influence of different institutional environments and economic and social characteristics in different regions [4]. Therefore, a further heterogeneity analysis is conducted from four aspects: region, agricultural production zone, environment, and educational resources.

4.1. Regional Heterogeneity

Cities across different regions exhibit substantial variations in scale, institutional environment, and resource endowments [4,8,11,25]. Consequently, the impact of agricultural green development pilot zones on agricultural green TFP might differ based on regional contexts. To investigate this variability, the city samples are categorized into three sub-samples corresponding to the eastern, western, and central regions of China, and the benchmark model is applied separately to each sub-sample. The results, presented in columns (1) to (3) of Table 8, indicate that the positive effects of agricultural green development pilot zones

on agricultural green TFP are primarily observed in the eastern and central regions. In contrast, the analysis shows no significant effect in cities within the western region.

Table 8. Heterogeneity analysis: results of regional and production zone heterogeneity.

	(1)	(2)	(3)	(4)	(5)
Variable	**Regional Heterogeneity**			**Production Zone Heterogeneity**	
	Eastern Region	**Western Region**	**Central Region**	**Agricultural Main Production Zone**	**Non-Agricultural Main Production Zone**
Treat × Post	0.732 ***	−0.098	2.926 ***	3.013 ***	−0.029
	(0.08)	(0.20)	(0.82)	(0.90)	(0.06)
pgdp	0.106	0.765 *	−1.653 ***	−0.084	0.003
	(0.11)	(0.45)	(0.48)	(0.22)	(0.15)
third	−0.494	−0.294	−4.633 ***	−1.842 **	−0.635 *
	(0.54)	(0.94)	(1.12)	(0.81)	(0.38)
educ	−0.003	−0.020	0.050 *	0.003	−0.006
	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
urbanization	0.136 *	−0.132	0.350 *	−0.049	0.042
	(0.08)	(0.70)	(0.21)	(0.12)	(0.09)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Clustered standard errors are in parentheses.

4.2. Heterogeneity in Agricultural Main Production Zones

Agricultural main production zones typically possess superior agricultural production conditions and are primarily focused on supplying agricultural products [26,27]. Given these distinctions, the policy effects may differ between agricultural main production zones and non-agricultural main production zones. In China, the designated agricultural main production zones encompass seven regions: Northeast Plain, Huang–Huai–Hai Plain, Yangtze River Basin, Fenwei Plain, Hetao Irrigation District, South China, and Gansu–Xinjiang [26–29]. This study selects ten major provinces from these primary agricultural production zones as focal areas for agricultural production analysis. Furthermore, the samples are divided into two groups, those located within agricultural main production zones and those outside these zones, to explore the heterogeneity in different agricultural settings. The findings, illustrated in columns (4) and (5) of Table 8, reveal that the construction of agricultural green development pilot zones significantly enhances agricultural green TFP in the agricultural main production zones. Conversely, this positive effect is not observed in the non-agricultural main producing zones.

4.3. Heterogeneity in Educational Resources

The endowment of educational resources in a region can significantly influence the effectiveness and efficiency of policy implementation, thus affecting the magnitude of policy impact [30–33]. It is hypothesized that regions with richer educational resources may experience a stronger promoting effect from the agricultural green development pilot zones on agricultural green TFP. To investigate this, the number of secondary vocational education schools is employed as an indicator of educational resources. The sample cities are categorized into three groups—low, medium, and high educational resources—based on the 30th and 60th percentiles of the number of secondary vocational education schools in each city. This classification facilitates a heterogeneity analysis. The results of this analysis are presented in columns (3) to (5) of Table 9. Accordingly, the coefficient of the interaction term is only significant at the 1% level in the high-educational-resources group. In contrast, the coefficients for both the low- and medium-educational-resources groups are not statistically significant. This indicates that the construction of agricultural green development pilot zones significantly boosts agricultural green TFP only in cities with high educational resources. Conversely, in cities with lower educational resources, the pilot zones do not significantly impact agricultural green TFP.

Table 9. Heterogeneity analysis: results of environmental and educational heterogeneity.

Variable	(1)	(2)	(3)	(4)	(5)
	Environmental Heterogeneity			Heterogeneity in Educational Resources	
	High Pollution	Low Pollution	Low Educational Resource	Medium Educational Resource	High Educational Resource
Treat × Post	3.277 ***	−0.030	−0.123	0.167	1.859 ***
	(1.03)	(0.08)	(0.16)	(0.19)	(0.42)
pgdp	−0.834 **	0.172	0.205	−0.254	−0.163
	(0.42)	(0.14)	(0.29)	(0.32)	(0.31)
third	−5.093 ***	−0.192	−0.926	−1.924	−2.907 ***
	(1.45)	(0.43)	(0.75)	(1.26)	(1.04)
educ	−0.005	−0.004	−0.011	0.074 *	0.016
	(0.02)	(0.01)	(0.04)	(0.04)	(0.01)
urbanization	0.441 **	−0.034	0.188	0.040	−0.091
	(0.17)	(0.09)	(0.56)	(0.19)	(0.11)
student	0.057	0.135	0.013	0.403	−0.025
	(0.22)	(0.12)	(0.43)	(0.32)	(0.14)
_cons	−92.243	−72.062 ***	−104.170 **	−38.200	−21.672
	(76.28)	(23.02)	(42.70)	(78.09)	(54.73)
city-fixed effects	controlled	controlled	controlled	controlled	controlled
year-fixed effects	controlled	controlled	controlled	controlled	controlled
N	720	1674	801	801	792
F	96.590	6.324	3.047	1.587	37.787
R^2	0.553	0.104	0.104	0.094	0.331

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Clustered standard errors are in parentheses. _cons is the abbreviation for constant.

4.4. Environmental Heterogeneity

Agricultural production activities are influenced by environmental conditions, and variations in pollution levels across regions can affect agricultural green TFP [34–36]. To examine environmental heterogeneity, this study classifies regions based on the levels of agricultural non-point source pollution recorded in 2016. Regions with higher levels of such pollution are designated as high-agricultural-pollution areas, while those with lower levels are categorized as low-pollution areas. The results of this environmental heterogeneity analysis are presented in columns (1) and (2) of Table 9. The coefficient of treat × post in the high-pollution group is significantly positive at the 1% level. Conversely, the coefficient of the interaction term in the low-pollution group is not significant, even at the 10% level. This suggests that the construction of agricultural green development pilot zones significantly enhances agricultural TFP in these areas with higher pollution levels. However, in cities with lower pollution levels, the pilot zones do not have a discernible impact on agricultural green TFP.

5. Conclusions and Suggestions

5.1. Conclusions

Based on the DID model analysis of 130 pilot zones in China, it is found that the implementation of agricultural green development pilot zones has substantially reduced non-point source pollution in agriculture within these zones while simultaneously enhancing TFP and preserving agricultural added value. The efficacy of this policy is further validated by several rigorous tests: the no-anticipation effect test, the parallel trend test, and the placebo test. Together, these tests confirm that there were no pre-existing differences in agricultural green TFP among the regions prior to policy implementation, thereby ensuring that the observed effects are not attributable to random fluctuations. In terms of regional heterogeneity, the impact of the policy is notably more pronounced in the eastern and central regions, as well as in the main agricultural production zones, compared to other areas.

Additionally, the policy tends to yield more significant benefits in regions characterized by higher levels of initial environmental pollution and more substantial educational resources.

5.2. Suggestions

Firstly, it is imperative to continue refining agricultural development policies by bolstering the construction of a comprehensive, sustainable, and strategic agricultural policy framework. Future policies aimed at promoting agricultural green development should not only increase in intensity but also clearly define their primary goal as fostering sustainable agricultural practices. This approach should also focus on enhancing the integration of and synergy between various policy measures. Secondly, significant emphasis should be placed on fostering agricultural green industrial clusters within the realm of agricultural green development. This involves prioritizing the research and development of technologies that support sustainable agricultural practices and cultivating an awareness of green development principles among agricultural producers. Thirdly, the rigorous implementation of policies is essential. The fundamental direction toward green development in agriculture must be steadfastly maintained. Enhancing the supervisory framework for green agricultural practices is crucial; this includes monitoring agricultural activities from multiple perspectives and developing a comprehensive system to assess, monitor, and evaluate the levels of green development in agriculture. Finally, regions that have achieved higher levels of agricultural green development should be leveraged to exert a radiating and driving influence on the surrounding areas. Local governments are encouraged to maximize their governance capabilities, tailor their policies to reflect the specific circumstances of their jurisdictions, and craft agricultural green development strategies suited to local conditions.

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