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Rural e-commerce and agricultural total factor productivity: Evidence from China

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Abstract: Employing the Comprehensive Demonstration of E-commerce in Rural Areas (CDERA) policy as a quasi-natural experiment, this paper explores the impact of rural e-commerce development on agricultural total factor productivity (ATFP) and its underlying mechanisms, using a difference-in-differences model. The analysis utilises panel data from 1 495 counties in China from 2001 to 2021. The findings indicate that the CDERA policy implementation enhanced ATFP in treated counties by approximately 1.6 percentage points compared to control counties, other factors being equal. Mechanism analysis further reveals that the CDERA policy enhances ATFP by improving agricultural technological efficiency and fostering agricultural industrial development. This study highlights the significant role of CDERA policy in enhancing agricultural productivity in China and offers policy insights for advancing rural e-commerce and promoting sustainable agricultural development.

Keywords: agricultural production efficiency; counties; industrial policy; rural e-commerce

Since the 21st century, emerging technological forces such as information and communications technology, data science, and artificial intelligence have developed rapidly, propelling the world into a new technological era. Driven by these rapid advancements in information technology, e-commerce has swiftly gained popularity worldwide, becoming an important means of stimulating economic growth and improving productivity. As the world's largest and most dynamic e-commerce market, China has always attached great importance to the development of the Internet and e-commerce. It has actively promoted e-commerce throughout the country to foster structural transformation and the upgrading of the national economy. Consequently, e-commerce and its related industries have gradually become key drivers in promoting this structural transformation. In this context, rural e-commerce emerged. In 2014, the Ministry of Commerce and the Ministry of Finance introduced the 'Comprehensive Demonstration of E-commerce in Rural Areas' (CDERA) policy.

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With the support of successive supportive policies, China's rural e-commerce and its service system have made substantial progress. By July 2022, the CDERA policy had cumulatively supported a total of 1 489 counties, and more than 2 600 county-level e-commerce public service and logistics centres had been established. Express delivery services have been continuously extended to rural communities, reaching over 80% of villages. In 2022, the country supported the upgrading and transformation of 878 retail markets for agricultural products, built 12 public welfare wholesale markets for agricultural products, added 960 000 tons of cold storage capacity, and improved the multi-level agricultural product circulation pattern of the 'backbone wholesale market + retail market + agricultural product e-commerce'. In summary, the CDERA policy not only provides new sales channels for agricultural products, breaks down the traditional barriers to circulation, and reduces transaction costs, but also improves the technical level of agricultural production and optimises the structure of the agricultural industry through the wide application of information technology.

However, since the turn of the new century, the agricultural development in China has faced two major constraints: increasing resource and environmental constraints, and insufficient support from agricultural science and technology. On the one hand, while the extensive agricultural development model has made significant contributions to ensuring China's food security, it has also caused problems such as the depletion and pollution of soil and water resources. On the other hand, there is a lack of support from modern agricultural technology and material equipment, including a shortage of agricultural machinery, which puts the agricultural technology sector at risk of being 'stifled'. Therefore, in the current context of increasing natural resource constraints, a deteriorating ecological environment, and the urgent need to transition and enhance the quality of agriculture, can the CDERA policy contribute to improving agricultural production efficiency?

This paper relates to two main strands of literature. The first strand concerns the economic and social impact of rural e-commerce development. Studies have analysed the economic and social impacts of rural e-commerce development (RECD) from different perspectives, including the impacts of e-commerce expansion on consumption inequality among rural households (Fan et al. 2018; Luo et al. 2019), increases in farmers' incomes (Li and Qin 2022), the economic growth of counties (Qin et al. 2023), and environmental improvement (Wei et al. 2023; Hunjra et al. 2024).

The second strand of literature relevant to this paper examines the factors influencing agricultural total factor productivity (ATFP). The influencing factors of ATFP in the existing literature can be categorised into four main groups: economic, social, policy and environmental. Among them, economic factors include financial inclusion (Hu et al. 2021), digital economy (Hu et al. 2024), agricultural trade (Xu et al. 2023), and other factors; social factors include labour force and land input growth (Sheng et al. 2019), farm irrigation facilities (Li and Liu 2023), an ageing labour force (Tong et al. 2024), and others; and policy factors include environmental regulation (Wang and Qian 2024), farmland leasing (Zhang et al. 2023), and others; and environmental factors include climate change (Li and Liu 2023), and others.

In summary, there is still a relative lack of research on the impact of RECD on ATFP and its underlying mechanisms. As the benefits of e-commerce policies have gradually materialised, rural e-commerce has shown great potential in promoting improvement in agricultural technology efficiency and the transformation of the rural economic structure (Liu et al. 2021; Zhang et al. 2023). Nevertheless, in the context of a deteriorating ecological environment and increasing natural resource constraints, whether rural e-commerce can incentivise the growth of local ATFP and thus promote agricultural transformation has not yet been adequately examined.

Compared with existing studies, the marginal contributions of this paper are primarily twofold. First, the economic effects of CDERA policy are studied from the perspective of agricultural total factor productivity, in the hope of providing a new theoretical and practical basis for assessing the role played by CDERA policy in promoting agricultural modernisation. Secondly, based on the perspectives of technical efficiency and industrial guidance, this study constructs a systematic theoretical analysis framework, which elaborates on the mechanisms by which RECD affects ATFP.

MATERIAL AND METHODS

Data

The data on CDERA policy from 2014 to 2021 used in this paper are sourced from the list of demonstration counties published on the website of the Ministry of Commerce. The Ministry of Finance of the People's Republic of China and the Ministry of Commerce

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of the People's Republic of China formulated an overall programme for the demonstration work and determined the demonstration provinces and districts by considering the degree of economic development, the e-commerce infrastructure, regional balance, and other factors. Each province could select no more than seven counties for demonstration through competitive allocation and develop specific implementation programmes on a county-by-county basis. Agricultural input and output and other economic data at the county level are obtained from the China Economic Information Network, China Statistical Yearbook for Counties, China Statistical Yearbook for Rural Areas, statistical yearbooks, and statistical bulletins of provinces, cities, and counties. The data on regional public brands of agricultural products originate from the website of the Ministry of Agriculture and Rural Development of the People's Republic of China. These data collectively form unbalanced panel data for 1 493 county-level administrative districts in China from 2001 to 2021. Considering the varying inflation rates across different provinces and to eliminate the influence of price factors, this paper takes 2000 as the base period to adjust all variables measured in monetary terms according to the consumer price index (CPI) of the province where they are located, to obtain their real value level. Finally, to deal with the impact of outliers and extreme values in the sample on the estimation results, this paper winsorises all continuous variables at 1% level. This process resulted in 24 653 observations remaining.

Variable

Agricultural total factor productivity. The dependent variable of the model is *ATFP*. Referring to Gong (2018), this paper uses the number of employees in agriculture, forestry, animal husbandry, and fisheries (10 000 people), the total sown area of crops (hectares), the net amount of agricultural fertiliser applied (tonnes), and the total power of agricultural machinery (10 000 kilowatts) as the input variables. The total output value of agriculture, forestry, animal husbandry, and fisheries (USD 100 million, calculated at constant 2 000 prices) is chosen as the output variable. Meanwhile, stochastic frontier analysis (SFA) and the Malmquist productivity index are used to measure and decompose county-level *ATFP*. Compared with Data Envelope Analysis, SFA has the advantage of incorporating a random disturbance term to control for the effects of measurement error and uncertainty. Since the agricultural industry is strongly affected by uncertainties such as the natural environment, the adoption of SFA is more in line with the essential characteristics of agricultural production (Gong 2018). In addition, when studying production efficiency in agriculture, it is important to consider the consistency of the theory, flexibility and the correct choice of the production function (Saur and Frohberg 2006). The SFA form is more flexible and can account for random phenomena present in the production activities, which can effectively avoid the bias arising from functional misspecification. Therefore, this paper adopts the SFA-Malmquist index method to measure the *ATFP* in each county. Referring to Kumbhakar and Lovell (2000), the SFA model is specified as follows:

$$\ln Y_{it} = \ln f(X_{it}, t; \beta) + \nu_{it} - \mu_{it} \tag{1}$$

where: Y_{it} – the agricultural output of county i in period t; X_{it} – agricultural factor inputs in county i in period t; β – the parameter to be estimated; f – a specific function form; ν_{it} – the random error term, which is assumed to follow a normal distribution, $\nu_{it} \sim N(0, \sigma_v^2)$; μ_{it} – the technical inefficiency term, which is assumed to follow a truncated normal distribution, $\mu_{it} \sim N^{+}(\mu, \sigma_v^2)$. ν_{it} and μ_{it} are independent of each other; a time-varying model was used to measure μ_{it}.

For the choice of the functional form f, this paper refers to Greene (2005) and selects the transcendental logarithmic function to construct the panel effects SFA model, the specific functional form is as follows:

$$\begin{aligned} \ln Y_{it} &= \beta_0 + \sum_j \beta_j \ln X_{it} + \beta_t t + \sum_j \sum_l \beta_{jl} \ln X_{ilt} \times \ln X_{ilt} + \\ &+ \beta_{tt} t^2 + \sum_{jt} \beta_{jt} t \times \ln X_{ijt} + \alpha_i + \nu_{it} - \mu_{it} \end{aligned} \tag{2}$$

where: i and t – county and year, respectively; j and l – the j^{th} and l^{th} factor inputs, respectively, α_i – an unobservable county fixed effect.

In order to satisfy the constant returns to scale (CRS) assumption and conform to the symmetry of the transcendental logarithmic function, this paper normalises the input and output variables of the model using land inputs. Specifically, the output variable is the agricultural output per unit of land (Y), and the input variables include the inputs of labour per unit of land (L), machinery inputs per unit of land (K), and fertiliser inputs per unit of land (M). These normalised input and output variables are then substituted into Equation (2) to obtain the following regression model:

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$$\ln Y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 \ln M_{it} + \beta_4 (\ln L_{it})^2 + \\ + \beta_5 (\ln K_{it})^2 + \beta_6 (\ln M_{it})^2 + \beta_7 \ln L_{it} \times \\ \times \ln K_{it} + \beta_8 \ln L_{it} \times \ln M_{it} + \beta_9 \ln K_{it} \times \ln M_{it} + \\ + \beta_{10} t \ln L_{it} + \beta_{11} t \ln K_{it} + \beta_{12} t \ln M_{it} + \beta_{13} t + \\ + \beta_{14} t^2 + \alpha_i + v_{it} - \mu_{it} \quad (3)$$

After estimating the model parameters, the technical efficiency (*TE*) of county *i* agriculture in period *t* can be obtained through the following equation:

$$ATE_i^t = \exp(-\mu_{it}), 0 \le \exp(-\mu_{it}) \le 1 \quad (4)$$

The agricultural technical efficiency (*ATE*) of county *i* from period *t* to period *t* + 1 can be calculated by the following equation:

$$ATE_t^{t,t+1} = \frac{TE_i^{t+1}}{TE_i^t} \quad (5)$$

The technological change in county *i* from period *t* to period *t* + 1 can be calculated by taking the partial derivative of *t* with respect to the estimated parameters of Equation (3). Due to the neutrality of technological change, it is appropriate to take the geometric mean of the agricultural technological progress (*ATP*) in adjacent periods *t* and *t* + 1, which is calculated as follows:

$$ATP_i^{t,t+1} = \sqrt{(1 + \frac{\partial f(X_{it}, t; \beta)}{\partial t})(1 + \frac{\partial f(X_{i(t+1)}, t+1; \beta)}{\partial (t+1)})} \quad (6)$$

Under the CRS assumption, based on the decomposition of the Malmquist productivity index, agricultural total factor productivity (*ATFP*) can be expressed as:

$$ATFP_i^{t,t+1} = ATP_i^{t,t+1} \times ATE_i^{t,t+1} \quad (7)$$

The parameter estimation results of the stochastic frontier production function are shown in Supplementary Table S1. To explore the trends in *ATFP* by county before and after the implementation of the policy, this paper statistically describes the distribution of *ATFP* kernel densities in counties that implemented the CDERA policy and those that did not, relative to all counties nationwide. As shown in Figure 1, the distribution of *ATFP* in counties that implemented the CDERA policy is to the right of that for all counties nationwide, while the distribution of *ATFP* in counties that did not implement the CDERA policy is to the left of the national distribution. This suggests a significant difference in *ATFP* between the two groups. On this basis, this paper will further explore the effect of CDERA policy on *ATFP* and its mechanism of action.

Rural e-commerce development. The core independent variable is the rural e-commerce development (*RECD*). For a county that implements the CDERA policy, *RECD* = 1 in the year of implementation and in subsequent years, otherwise, *RECD* = 0.

Control variables. In this paper, referring to the existing studies (Gong 2020; Su et al. 2023) the control variables are mainly divided into three categories. First, geographic conditions, including topographic relief and average elevation. Second, economic conditions, includ-

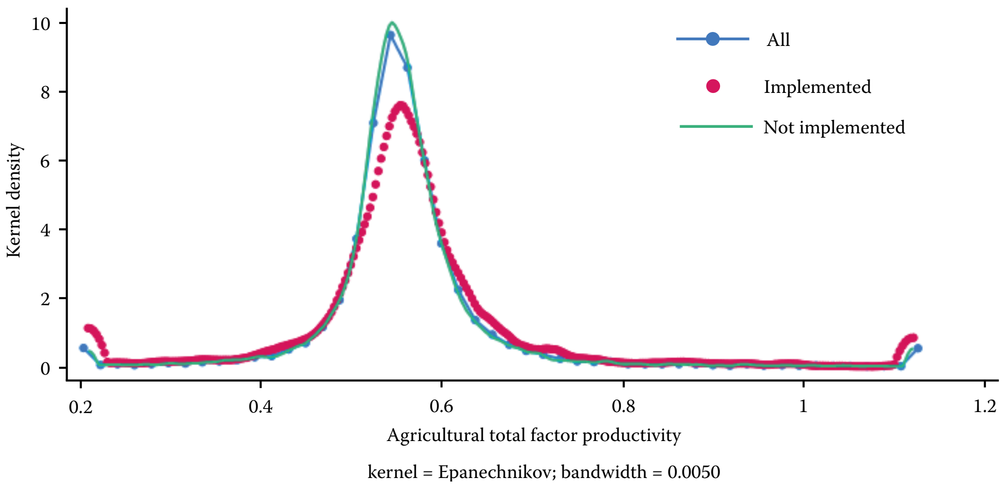

Figure 1. Total factor productivity in agriculture by county

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ing industrial structure, human capital level, the level of government intervention, the level of infrastructure, and the level of brand development. Among them, the industrial structure is expressed as the proportion of the value added of the secondary industry in GDP. The human capital level is measured by the proportion of pupils enrolled in ordinary middle schools relative to the total population at the end of the year. The level of government intervention is expressed as the ratio of local government budget expenditure to GDP. The level of infrastructure is expressed as the logarithm of the number of fixed-line telephone subscribers. The level of brand development is measured by the number of public agricultural product brands in the county. Third, agricultural production conditions, including the level of agricultural development, planting structure, average annual rainfall, and average annual temperature. The level of agricultural development is the proportion of the added value of the primary industry in GDP, and the planting structure is the proportion of the grain sown area to the total sown area.

The variables employed in this paper and their descriptive statistics are shown in Table 1.

Model

Benchmark regression model. The CDERA policy, initiated in 2014, has been driven by the Ministry of Commerce of the People's Republic of China (MOFCOM) and implemented in a top-down manner. Specifically, guided by the relevant documents of the MOFCOM, each province could select no more than seven counties for demonstration through competitive allocation and formulate a specific implementation programme on a county-by-county basis. This represents an exogenous reform promoted by the MOFCOM through its administrative power, so the CDERA policy can be regarded as a quasi-natural experiment. In addition to the top-down administrative driving force, the CDERA policy has to be carried out in accordance with criteria set by the Ministry of Commerce. Consequently, whether a region can become a comprehensive demonstration county of e-commerce in rural areas, and the timing of its designation, mainly depends on the degree of local economic development, existing e-commerce infrastructure, regional balance, and other factors; local ATFP is not a major decision-making factor. This allows this paper to use the difference-in-differences (DID) model to analyse the impact of CDERA policy on *ATFP.*

As point in time at which each county becomes a CDERA designated county varies, the multi-period DID model is particularly suitable. This model allows for the flexible definition of treatment group and control group according to the specific timelines of policy implementation in each region, thereby overcoming potential inaccuracies associated with using simple year dummy variables in a traditional DID model. Therefore, this paper adopts the multi-period DID

Table 1. Descriptive statistics of the main variables

Variables	Definition	Mean	SD
ATFP	specific calculations are shown in equation (7)	0.556	0.086
RECD	county is a RECD in that year = 1; otherwise = 0	0.132	0.338
Agricultural development level	value added of primary sector/county GDP	0.229	0.129
Industrial structure	value added of secondary sector/county GDP	0.414	0.155
Human capital level	number of students in school/total county population	0.054	0.018
Government intervention level	public financial expenditure/county GDP	0.229	0.208
Infrastructure level	logarithm of the number of fixed telephone subscribers	10.495	1.099
Planting structure	area sown in grain crops/total area sown in crops	0.671	0.170
Average annual rainfall	average annual rainfall in the county (m)	0.033	0.019
Average annual temperature	average annual temperature of the county (°C)	12.440	5.673
Brand development level	number of regional public brands of agricultural products in counties	0.558	1.259
Topographic relief degree	degree of topographic relief in the county (km)	0.893	0.984
Average elevation	average elevation of the county (m)	8.025	10.783

0 indicates that the number is less than 0.001; *ATFP* – agricultural total factor productivity; *RECD* – rural e-commerce development

Source: Author's compilation

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model to assess the impact of CDERA policy on *ATFP* and constructs the following multi-period DID model:

$$\ln ATFP_{it} = \alpha_0 + \alpha_1 RECD_{it} + \sum_{j=1}^{J} \beta_j X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (8)$$

where: $RECD_{it}$ – the implementation of CDERA policy of county i in year t; α_1 – the key coefficient, and if it is significantly positive, it indicates that CDERA policy is conducive to improving county *ATFP*; $AFTP_{it}$ – the *ATFP* at county level; α_0 – the constant term; X_{it} and β_j – the control variable and its coefficient, respectively; μ_i and δ_t – county fixed effects and year fixed effects, respectively; ε_{it} – the random error term.

Parallel trend test model. To examine whether the treatment group and the control group exhibit parallel trends prior to the CDERA policy intervention, Equation (8) is extended to construct a dynamic DID model. This allows us to test whether the parallel trend assumption is satisfied. Consequently, we specify the following dynamic DID model:

$$\ln ATFP_{it} = \alpha_0 + \sum_{k=2}^{K} F_k RECD_{i,t-k} + \\ + \sum_{m=0}^{M} L_m RECD_{i,t+m} \sum_{j=1}^{J} \beta_j X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (9)$$

where: $RECD_{\mathrm{i,\,t-k}}$ – the dummy variable for the period k (k = 2, ..., K) before the implementation of CDERA policy; $RECD_{i,t+m}$ the dummy variable for the period m (m = 0, 1, ..., M) after the implementation.

If the coefficient for the pre-treatment period is not significant, but the coefficient for the post-treatment period is significant (or at least some are significant), then the parallel trend assumption is satisfied, and the policy has an impact on the *ATFP*. Other variables are defined consistently with those in Equation (8).

Mechanism test model. Considering the traditional mediation effect model, including both mechanism variables and core explanatory variables in the same regression simultaneously may lead to endogeneity problems. This paper draws on the method of Chen et al. (2020) and mainly examines the influence of the core explanatory variables on the mechanism variables to verify the proposed mechanism. The specific methods are as follows:

$$MedVar_{it} = \alpha_0 + \gamma_1 RECD_{it} + \sum_{j=1}^{J} \beta_j X_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (10)$$

where: $MedVar_{it}$ – the mechanism variable, and it is sequentially replaced with variables reflecting the Agricultural technical efficiency, agricultural chain extension, agricultural structure advancement, and scale effect; γ_1 – the parameter to be estimated.

If the *RECD* variables have a significant effect on the mechanism variables, the mechanism of action is verified.

RESULTS AND DISCUSSION

Benchmark regression

Table 2 reports the benchmark regression results that estimate the impact of CDERA policy on ATFP. Column (1) considers only the *RECD* variable and controls for year and county fixed effects. Natural geographic conditions have long influenced the basis of agricultural production; different topographic features affect soil quality, precipitation distribution, and temperature changes, which in turn affect the growing conditions and productivity of crops. Therefore, this paper further introduces an interaction term between geographic conditions and time trend variables in column (2). Furthermore, column (3) includes all control variables. According to these results, the *RECD* coefficients are all significantly positive at the 5% level. The results in column (3) indicate that the implementation of the CDERA policy increased *ATFP* in treatment counties, relative to control counties, by approximately 1.6%, *ceteris paribus*.

A possible explanation is that the implementation of the CDERA policy has been accompanied by government investment and policy support for rural infrastructure (Zhao et al. 2024), such as internet penetration and logistics network construction. A sound logistics system can effectively reduce time costs and losses in the distribution of agricultural products, increase overall supply chain efficiency, and improve ATFP (Dhehibi et al. 2016; Goldfarb and Tucker 2019). At the same time, an improved logistics system expands the market scope of agricultural products, eliminates the cost for traditional retailers to enter the offline market, and reduces the impact of distance on trade costs. Thus, it can increase the volume of trade between cities and improve market coverage and competitiveness (Fan et al. 2018; Luo et al. 2019). In addition, the development of rural e-commerce has facilitated the-optimisation of the supply chain, reducing the cost of intermediate links from production to market for agricultural products through more efficient logistics and distribution systems (Goldfarb and Tucker 2019).

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Table 2. Benchmark regression results

Variables	ln*ATFP*			
	(1)	(2)	(3)	(4)
RECD (0.005)	0.012**	0.014***	0.016***	0.015***
	(0.005)	(0.005)	(0.005)	–
Agricultural development level	–		0.279***	0.275***
		(0.037)	(0.037)	–
Industrial structure	–		0.006	0.002
		(0.024)	(0.024)	–
Human capital level	–		0.257**	0.273**
		(0.108)	(0.108)	–
Government intervention level	–		–0.021	–0.025
		(0.016)	(0.016)	–
Infrastructure level	–		0.007**	0.007**
			(0.003)	(0.003)
Planting structure	–		0.038*	0.0375*
		(0.020)	(0.020)	–
Average annual rainfall	–		–0.370**	–0.357**
		(0.144)	(0.144)	–
Average annual temperature	–		–0.022***	–0.022***
		(0.004)	(0.004)	–
Brand development level	–		–0.000	–0.000
		(0.001)	(0.001)	–
CPRP	–		–	–0.006
				(0.009)
APQSC	–		–	0.011**
				(0.005)
LC	–		–	–0.026***
				(0.009)
CECDPZ	–		–	0.004
				(0.004)
Topographic × *T*	no	yes	yes	yes
Elevation × *T*	no	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
County fixed effects	yes	yes	yes	yes
n	24 653	23 328	23 206	23 206
R^2	0.166	0.167	0.175	0.175

***, ** and *significance at 1%, 5% and 10% levels, respectively; robust standard errors are in parentheses; 0.000 indicates that the number is less than 0.001; *APQSC* – agricultural product quality and safety county; *ATFP* – agricultural total factor productivity; *CECDPZ* – cross-border e-commerce comprehensive demonstration pilot zones; *CPRP* – county-based poverty reduction policy; *LC* – low-carbon city; *RECD* – rural e-commerce development; *T* – time trend term
Source: Author's compilation

In addition to the CDERA policy intervention during the sample period, other policies were also implemented, such as the county-based poverty reduction policy (CPRP), the agricultural product quality and safety county (APQSC), low-carbon city (LC) schemes, and cross-border e-commerce comprehensive demonstration pilot zones (CECDPZ). To avoid the influence of other policies implemented concur-

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rently, which could introduce confounding factors and prevent the identification of a clear causal effect, this paper incorporates dummy variables for the aforementioned four policies, based on Equation (8). The regression results are subsequently shown in column (4) of Table 2. Controlling for the other policy interventions, the *RECD* coefficient is still significantly positive at the 1% level. Excluding other policy interferences, the implementation of the CDERA policy increased *ATFP* in treatment counties relative to control counties by about 1.5%, *ceteris paribus*.

Robustness tests

The results of the previous analysis showed that CDERA policy had a significant positive effect on *ATFP*. To further clarify the robustness of the benchmark regression results, this paper conducts a series of robustness tests.

Parallel trend test. The premise for an unbiased estimation using the DID model is that the *ATFP* levels of the counties in the treatment group and the control group should meet the assumption of parallel trends before the exogenous shock. Therefore, to test the validity of the estimated results, this paper combines the event study method to test the dynamic effect of CDERA policy.

Figure 2 displays the estimates of $RECD_{i,t-k}$ and $RECD_{i,t+m}$ at 95% confidence intervals. The results show that none of the coefficients of the *RECD* variables significantly deviate from zero before the implementation of the policy, indicating that the model used satisfies the parallel trend assumption. The CDERA policy did not have a significant impact on agricultural total factor productivity during the first year of its implementation but began to produce a significant impact in the second year, which became insignificant in the fourth year. This is mainly due to the following: firstly, in the initial period of the policy, time is required for infrastructure development, technology diffusion and personnel training, and farmers and relevant departments need to adapt to the new model, so the effect is not obvious in the first year. Secondly, the construction of logistics, networks and other infrastructures takes time, and the policy was not yet fully developed in the first year of its implementation, affecting the promotion and application of e-commerce; its effects only began to materialise in the second year. Finally, after e-commerce penetration in rural areas reaches a certain level, the market tends to become saturated, the growth of new users and transactions slows, and the stimulative effect on productivity diminishes.

Placebo test. To avoid potential bias from unobservable omitted variables, we conduct a placebo test to further verify the robustness of the benchmark regression results. The first step is the spatial placebo test. The placebo test is carried out by reassigning counties to the treatment group to assess the authenticity of the impact of CDERA policy on *ATFP*. Based on the idea of a counterfactual test, this paper randomly selects 927 counties out of 1 493 sample coun-

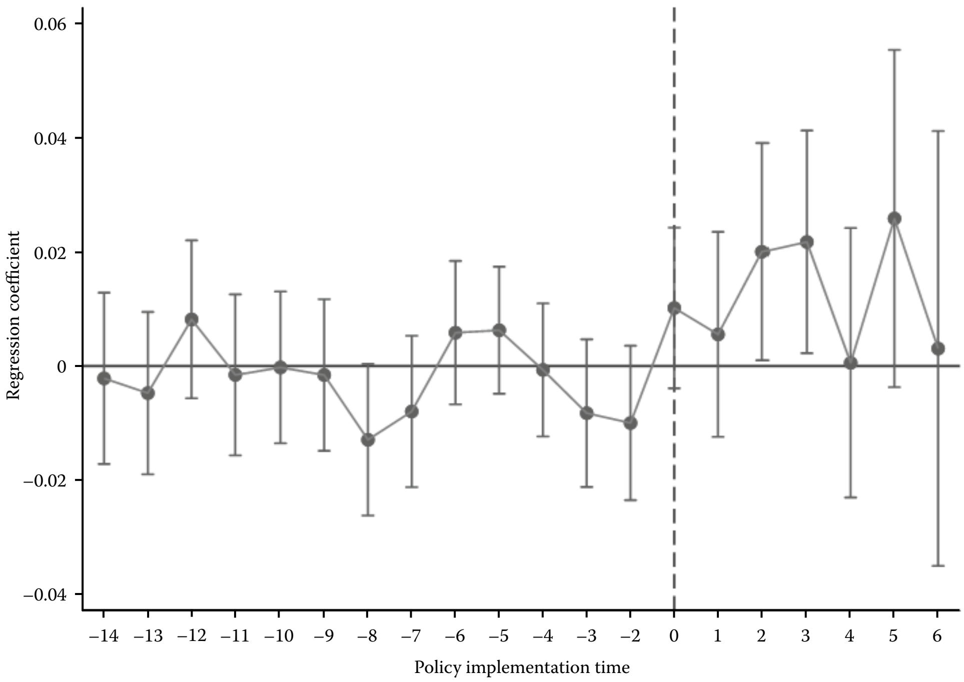

Figure 2. Parallel trend test

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ties to constitute the 'pseudo-treatment group', and the remaining 566 counties as the 'pseudo-control group', to obtain the coefficient estimates of *RECD* variable by implementing this spatial placebo. This process is repeated 1 000 times to obtain 1 000 regression coefficients and their corresponding *P*-values. Table 3 reports the two-sided, left-tailed, and right-tailed *P*-values of the spatial placebo test. According to these results, the *P*-values for the two-sided and the right-tailed test are less than 0.05, meaning the null hypothesis that the treatment effect is 0 is strongly rejected at the level of 1%. In addition, this paper also presents the kernel density plot and histogram of the spatial placebo effect (Figure 3), as well as the estimated value of the treatment effect (vertical line in the figure).

Goodman-Bacon decomposition. As the treatment effect in two-way fixed effect regressions is typically heterogeneous across treatment groups or treatment times, this may lead to the problem of 'bad treatment groups' or even negative weights. Therefore, the multi-period DID estimates may be biased under two-way fixed effects (Baker et al. 2022). To investigate the extent of bias in multi-temporal DID estimation under two-way fixed effects, this paper refers to Goodman-Bacon (2021) and decomposes the estimation results into a weighted average of the average treatment effects derived from three types of sub-samples. The decomposition categorises these comparisons into three types:

i) an 'early or late treated group' versus a 'never treated group',

ii) an 'early treated group' versus a 'late treated group', and

iii) a 'late treated group' versus an 'early treated group'.

Table 4 reports the results of the Bacon decomposition.

Table 3. Estimates of placebo test coefficients

Variables	coefficient	*P*-value		
		two-sided	left-sided	right-sided
RECD	0.016	0.014**	0.992	0.008***

*** and **significance at 1% and 5% levels, respectively; control variables are consistent with the baseline regressions; *RECD* – rural e-commerce development

Source: Author's compilation

Here, the desirable comparison types ('early treatment vs. later control' and 'treatment vs. never treatment') accounts for 99.987% of the total weight, while the potentially problematic comparison type ('later treatment vs. early control') accounting for only 0.013% of the total weight. The estimated coefficient of DID is greater than 0, and the weight of the problematic comparison component contributing to this estimate is only 0.009%. Thus, it can be inferred that the core findings of this study are highly robust to such potential biases.

Selectivity bias. To avoid bias in regression results due to sample selection issues, this paper adopts multi-temporal PSM-DID for robustness testing. As PSM (propensity score-matching) applies to cross-section data and DID applies to panel data, there are two main solutions approaches for their combination. One is to construct a cross-section PSM, whereby panel data are treated as cross-section data and then matched. The second approach involves period-by-period matching, following Böckerman and Ilmakunnas (2009). Thus, this paper adopts cross-sectional PSM and period-by-period matching methods for propensity score matching, respectively. The specific operation is as follows: first, set the 9 control variables in column (3) of Table 2

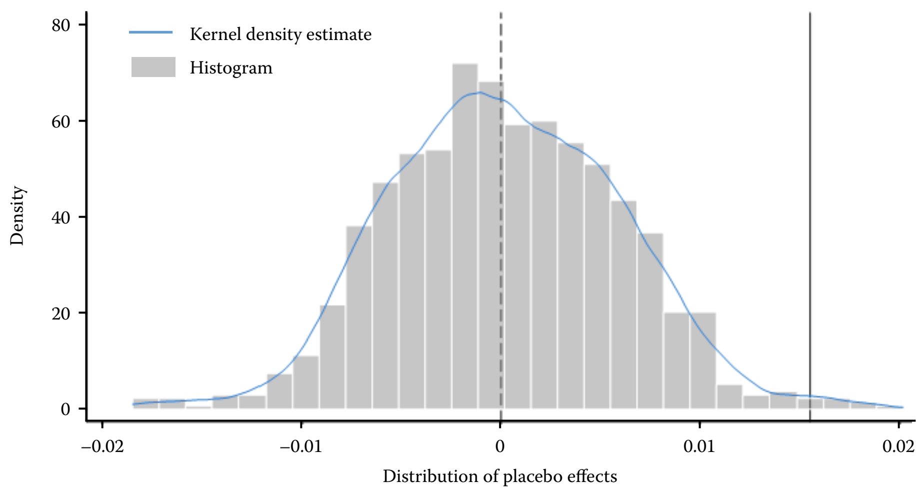

Figure 3. Placebo test

Source: Author's compilation

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Table 4. Bacon decomposition estimation results

DID grouping of different sub-samples	DID estimates	Weight (%)
Early treatment vs. later control	0.000	33.020
Treatment vs. never treatment	0.020	66.967
Later treatment vs. early control	0.154	0.013

0.000 indicates that the number is less than 0.001; DID – difference in differences

Source: Author's compilation

Table 5. PSM-DID estimation results

Variables	(1)	(2)
	cross-sectional PSM	period-by-period PSM
RECD	0.015***	0.012**
	(0.006)	(0.005)
Control variables	yes	yes
Fixed effect	yes	yes
Observed value	23 317	22 637
R^2	0.175	0.179

*** and **significance at 1% and 5% levels, respectively; robust standard errors are in parentheses; control variables are consistent with the baseline regressions; PSM-DID – propensity score matching difference in differences; *RECD* – rural e-commerce development

Source: Author's compilation

as covariates and match them using the 1:1 nearest-neighbor matching method. The caliper range is 0.01. Second, the balance test is conducted. The results show that for the cross-sectional PSM, the differences in all variables are significantly reduced after matching, and all standardised errors are less than 10%. For the period-by-period matching method, all variables pass the balance test, indicating that the matching successfully reduces sample differences between the treatment and control groups. Finally, using two kinds of matching samples respectively, the treatment group and control group samples within the common support area are retained, and Equation (1) is re-estimated to obtain the regression results in columns (1 and 2) of Table 5. After PSM matching, the coefficient for the *RECD* variable is significantly positive at least at the level of 5%, which is not significantly different from the benchmark regression results.

Mechanism test

The results of the previous analysis indicate that CDERA policy has a significant and robust positive effect on *ATFP*. To clarify the mechanism of action by which the CDERA policy affects *ATFP*, further mechanism analysis is conducted in this paper.

Technical efficiency enhancement effect. Agricultural technical efficiency (ATE) and agricultural technological progress (ATP) are the main factors that increase ATFP (Lambert and Parker 1998; Shah et al. 2023). To verify the mechanism of technical efficiency improvement, this paper uses SFA to measure *ATE* and *ATP*. The regression results are shown in columns (1) of Table 6. The impact of the CDERA policy on *ATE* is significantly positive at the 1% level. Excluding other factors, the implementation of the CDERA policy increased *ATP*s in treatment counties relative to control counties by approximately 1.4%.

Table 6. Mechanism test results

Variables	(1)	(2)	(3)	(4)
	ATE	ACE	*ASA*	*SE*
RECD	0.014***	0.059***	0.015***	0.023***
	(0.005)	(0.019)	(0.004)	(0.008)
Control variables	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes
n	23 328	22 056	23 328	23 328
R^2	0.174	0.797	0.619	0.898

***significance at 1% level; robust standard errors are in parentheses; control variables are consistent with the baseline regressions; *ACE* – agricultural chain extension; *ASA* – agricultural structure advancement; *ATE* – agricultural technical efficiency; *RECD* – rural e-commerce development; *SE* – scale effect; *n*– observed value

Source: Author's compilation

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The improvement of ATE refers to the improvement of overall efficiency per unit of time in agriculture by improving the coordination between various resource elements and releasing greater potential under the existing technological level (Gao and Lyu 2023). A possible explanation is that the focus of the policy is mainly on the distribution and market segments, rather than directly on the innovation or research and development of agricultural production technology. Firstly, the funds and resources of the policy are mostly focused on the construction of e-commerce platforms and related supporting facilities (Zhao et al. 2024), while investment in agricultural technology R&D and innovation is relatively limited. Secondly, the CDERA policy empowers traditional banks and other financial institutions to more efficiently explore and centrally process large volumes of information and data. It reduces the information asymmetry between the banks and farmers and improves the effective allocation of financial resources (Lin et al. 2013). This will consequently improve access to finance for agricultural producers, especially small-scale farmers, and ease their financing constraints in the application of new equipment and technology (Lin et al. 2022).

Industry guidance effect. China's rural counties often lag in terms of development level, lack industrial momentum, and possess a single structure. RECD is beneficial for breaking through the traditional factor boundaries and introducing information as a new factor of production into the rural economic structure. These advantages not only promote the digital transformation of traditional industries in the countryside but also guide the rooting and growth of 'Internet+' in rural areas, promote the in-depth integration of rural primary, secondary, and tertiary industries, and aid the transformation of the county industrial structure (Leong et al. 2016).

To further explore how RECD drives these changes, we examine three mechanisms: agricultural chain extension (ACE), agricultural structure advancement (ASA), and scale effect (SE). Among them, *ACE* is expressed in terms of the development of agricultural producer services and is measured by the logarithm of the output value of agriculture, forestry, livestock, and fishery services, *ASA* is measured by the ratio of the agriculture, forestry, livestock and fishery services to the total value of agriculture, forestry, livestock, and fishery output, and *SE* is expressed by the logarithm of the per capita area of crop cultivation. Columns (2–4) of Table 6 sequentially report the regression results of the impact of CDERA policy on the extension of the agricultural industrial chain, the optimisation of the agricultural industrial structure and the scale effect. The results show that the *RECD* coefficients are significantly positive at least at the 5% level. This indicates that CDERA policy significantly promotes the extension of the agricultural industry chain, the advancement of the agricultural industry's structure, and the development of industrial scale.

First, the CDERA policy helps farmers directly connect to the market through the construction of e-commerce platforms and the improvement of the rural logistics system (Ji et al. 2023), which shortens the intermediate links and extends the agricultural industry chain. This result is consistent with existing literature, such as Chen et al. (2022), who also point out that e-commerce can effectively shorten the circulation link of agricultural products and increase the added value of agricultural products. Secondly, since 2015, one of the focuses of financial funding support in CDERA policy is to support the brand cultivation and quality assurance system construction of agricultural products and rural characteristic agricultural products for the RECD. The RECD has greatly increased the visibility of rural products and formed e-commerce-oriented industries and factor agglomerations (Galloway et al. 2011; Fan and Salas-Garcia 2018). Combining regional resource endowments and characteristic industries with digital technology, not only encourages agriculture to transform from traditional primary product production to diversified, high-value-added processing and modern agricultural services but also promotes the development of rural characteristic industries and rural industrial integration. This is consistent with the study of Lin et al (2016), where RECD has not only changed the traditional mode of agricultural production but also promoted diversification and high-end agricultural products. Finally, RECD has led to the upgrading of rural infrastructure, and the development of rural infrastructure can directly drive the collective progress of rural industries. It lowers the threshold of market entry, making it easier for small farmers and cooperatives to expand their production scale (Wang et al. 2023). It then facilitates the realisation of economies of scale and improves production efficiency as well as agricultural technical efficiency (Gao and Lyu 2023). The RECD enhances the connectivity and resource circulation efficiency of spatial networks in rural settlements through scale effects,

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traffic and informatisation levels, and the logistics development environment (Wang and Qian 2024). Excluding other factors, the implementation of the CDERA policy increased *ACE*, *ASA*, and *SE* in treatment counties relative to control counties by 5.9, 1.5, and 2.3%, respectively.

CONCLUSION

The CDERA policy, as a policy to support and benefit agriculture, has improved the efficiency of agricultural technology through infrastructure development and by optimising the allocation and use of factors of production, while at the same time promoting the development of the structure of the agricultural industry and increasing the comprehensive production capacity of agriculture. Against the background of frequent extreme weather and a deteriorating ecological environment, this paper discusses the impact of CDERA policy on agricultural total factor productivity using the SFA framework. The total factor productivity of agriculture is measured based on a stochastic production frontier model with variable coefficients, and the impact of CDERA on agricultural total factor productivity and its mechanism of action are analysed using the double difference model. The study finds that the implementation of the CDERA policy increases the *ATFP* in treatment counties relative to control counties by approximately 1.6%, not accounting for other factors. The CDERA policy improves the *ATFP* through technical efficiency enhancement and industrial guidance effects.

Based on the above conclusions, this paper offers the following policy insights. First, the RECD should be deepened to ensure sustainable growth in ATFP. To give full play to the effectiveness of CDERA policy and ensure multi-level and multi-dimensional e-commerce policies, the infrastructure construction in rural areas should be emphasised to build a good rural e-commerce ecosystem, including a comprehensive supply chain system, market docking mechanism, and after-sales service network. Second, according to the mechanism analysis results, the government and relevant departments should increase support for agricultural technology innovation and promotion, promote the development of the 'internet + agriculture' model, facilitate industrial upgrading and structural optimisation, and guide farmers to actively adopt e-commerce technology. Third, it is crucial to establish a systematic framework for replicating the successful CDERA model in other regions. This includes sharing best practices, providing tailored policy guidelines, and fostering inter-regional collaborations to ensure the scalability and adaptability of the model. Finally, addressing potential challenges in scaling up rural e-commerce, such as the digital literacy gap and infrastructure limitations, should be prioritised. This can be achieved through targeted initiatives, such as digital skills training programmes for farmers, public-private partnerships to improve rural internet connectivity, and incentives for private sector investment in rural e-commerce infrastructure. By implementing these measures, the long-term sustainability and broader impact of the CDERA policy can be significantly enhanced.

The limitations of this paper are: first, the agricultural production efficiency studied in this paper focuses only on the desired output of agricultural production and does not consider the existence of undesirable outputs, such as agricultural carbon emissions. Second, this paper mainly explores the direct effect of CDERA policy on agricultural total factor productivity and does not consider how its implementation might cause changes in the volume of inter-regional agricultural trade and consequently affect ATFP. Therefore, in future research, we will further consider the effect of CDERA policy on agricultural green total factor productivity. The spatial spillover effect of CDERA policy will also be further analysed.

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