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Can E-Commerce Adoption Improve Agricultural Productivity? Evidence from Apple Growers in China

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Abstract: E-commerce is not only a new channel through which farmers can sell agricultural products, but also an important engine for transforming agricultural development and modernizing agriculture in the era of the digital economy. Analyzing the adoption of e-commerce from the micro level to improve farmers' production efficiency has practical value. On the basis of theoretical discussion and analysis and on the survey data of 827 apple farmers in Shaanxi Province, China, we used propensity score matching (PSM) and stepwise regression to test the effects of e-commerce adoption on agricultural production efficiency and the mechanism through which these effects occur. The results showed that e-commerce adoption has a significant positive impact on agricultural production efficiency. The allocation of agricultural factors plays a mediating role in the impact of e-commerce adoption on agricultural production efficiency. Specifically, e-commerce adoption can effectively encourage farmers to rationally allocate agricultural labor, land, and capital production factors, promote the sustainable development of the environment and contribute to creating a harmonious community atmosphere. Therefore, we propose strengthening rural e-commerce support and the publicity and guidance regarding e-commerce adoption by farmers, holding e-commerce training, and promoting the popularization of rural e-commerce to help promote the modernization of agriculture.

Keywords: apple growers; e-commerce adoption; agricultural production efficiency; element configuration

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1. Introduction

Continuing to ensure stable agricultural production and supply, increase farmer income, and promote high-quality agricultural development, is crucial to ensuring farmer well-being. The key to achieving this goal is to improve agricultural production efficiency. Thus, exploring methods to improve agricultural production efficiency has long been the focus of scholars. The literature confirms that traditional factors, such as agricultural technology progress [1,2], land transfer [3–5], human capital accumulation [6,7], and agricultural investment [8,9], play an important role in increasing agricultural production efficiency. In recent years, China has implemented a strategy of informatization, to encourage a transition from traditional development to modern and sustainable development through network communication technology and modern science and technology, and to continuously improve the use of intelligent and digital technologies, so as to improve work efficiency, economic efficiency, and development quality [10]. With the adoption of the strategies, the impact of emerging production factors on agricultural production efficiency has also attracted extensive attention [11–14]. As a specific application of the Internet in the agricultural field, agricultural product e-commerce is developing increasingly rapidly. The 2022 China Agricultural Products E-commerce Development Report stated that in 2021, online retail sales in rural areas reached RMB 2050 billion (USD 293.97 billion, the exchange rate of RMB against USD on 6 December 2022 was 0.1434), with a year-on-year growth of 14.23% [15]. The state has successively issued a number of policies to encourage the development of agricultural e-commerce, considering it as an important means to promote the rise of agricultural products and increase farmer income. Analyses of the impact mechanism of agricultural e-commerce on agricultural production efficiency are required to not only increase the impact of the Internet on agricultural production efficiency, but also to enrich the methods used to improve agricultural production efficiency and to provide constructive suggestions for exploring the dynamic mechanisms through which agricultural production efficiency is achieved and the formulation of relevant policies of agricultural e-commerce.

Theoretical scholars have found that agricultural e-commerce can alleviate the constraints on farmer information, improve agricultural product sales and profit margins, substantially improve farmer income [16–18] and their sense of horizontal reality and vertical expected economic gain [19], effectively promote the two-way circulation of agricultural products and consumer goods, and increase the consumption of these products by rural residents [20]. However, few researchers have paid attention to the impact of agricultural e-commerce on agricultural production. As an effective means to marketize agricultural products, agricultural e-commerce will not only change the mode used to sell agricultural products and farmer income, but also extend the production chain upward to the production end, which will impact agricultural production [21]. Then, as an important indicator to measure agricultural performance, we need to determine how agricultural e-commerce affects agricultural production efficiency and the mechanism through which this occurs. Discussion on this topic is scarce in the literature. From Marx's social reproduction process of production, circulation, exchange, and distribution, the e-commerce of agricultural products impacts not only the circulation link, but also the production link and places stricter requirements on the organizational form and production capacity of upstream production [22]. We hypothesized that as a resource allocation mechanism [19], agricultural e-commerce is embedded in the local society in a process of interaction with other rural factors. Based on traditional land, labor force, capital, and other factors, it injects new production factors, alleviates restrictions on farmer information and resource constraints, and changes farmers' factor allocation behavior. The allocation of agricultural factors such as land [23], labor [24], and capital [25] should be optimized to positively impact agricultural production efficiency.

Apple is the most important fruit crop in China. As of 2020, apple orchards covered 31,327,800 mu (2,088,520 hectares), with an output of 41 million metric tons. Apple farming is the leading industry in some areas of China and the main source of income of local farmers. However, in recent years, apple sales in China have been facing considerable challenges [26]. The distribution of apples in the main producing areas is showing a trend of shifting westward and expanding northward. The area under apple planting in the dominant regions of the Loess Plateau has been continuously increasing in the past 20 years, whereas production in the Bohai Bay region has been continuously decreasing [27]. The apples sales market is mainly concentrated in the southeast coastal areas, so the distance between production and sales has widened. The areas conducive to apple production and deeply impoverished areas highly overlap, and most of them are at the end of an interwoven network of transportation, Internet, logistics, etc. In these areas, information is blocked, and apple sales are difficult, which restrict the sustainable improvement of agricultural production efficiency and the quality of life of farmers. Therefore, the impact of agricultural e-commerce on apple production efficiency must be explored to improve relevant policies.

Using data from 827 surveyed apple farmers in Shaanxi Province, we analyzed the mechanism through which agricultural e-commerce affects agricultural production efficiency. We then empirically tested the mediating role of agricultural factor allocation in the impact of agricultural e-commerce on agricultural production efficiency. Finally, we suggest policy frameworks to improve the participation in agricultural e-commerce.

2. Research Design and Research Hypothesis

2.1. Theoretical Basis

According to expected utility theory, farmers adjust production decisions according to the optimal expected price and income. According to bounded rational behavior theory, effective access to information can improve the rationality of farmers' decisions. The adoption of e-commerce enables farmers to have high expectations of agricultural income and receive more market feedback information, so as to improve farmers' enthusiasm for production. Moreover, the adoption of e-commerce achieves "digital empowerment" and improves farmers' ability to obtain information about various factors. In addition, as the most important resources in agricultural production, labor, land, and capital are interrelated and inseparable. Based on expected utility theory and bounded rationality theory, we considered the interaction between the three factors and examined the mechanism between e-commerce adoption, factor allocation, and agricultural production efficiency.

2.2. How E-Commerce Adoption Influences Agricultural Production Efficiency

Figure 1 depicts the mechanism through which e-commerce adoption affects agricultural production efficiency. First, e-commerce adoption can promote the optimization of agricultural labor allocation, thus improving production efficiency. E-commerce adoption can increase the sales volume and profit margin of agricultural products, thereby increasing the income expectation [16] and the degree of attention to agriculture [28]. According to Low's analysis of farmer behavior, given the existing labor and land factor market, if farmers partially participate in the market and a large amount of the agricultural labor force with food self-sufficiency choose to work, substantial differences will exist in the ability of each farm worker to obtain a wage, so workers need to make choices between farming and nonagricultural employment [29]. The income-increasing effect of e-commerce adoption encourages farmers to reconfigure their family labor structure, so that farmers with comparative advantages in their agricultural operations can increase the labor input and optimize the family labor allocation [30], which positively affects agricultural production efficiency. Additionally, e-commerce adoption can drive part of the population to return to farms [24], alleviate the rural labor shortages, and the returning labor force has increased personal development ability and comparative advantages in knowledge, skills, social network, and economic capital accumulation, so can provide information and technology feedback to local farmers. Therefore, e-commerce adoption can promote the flow labor force to rural areas, strengthen services provided to farmers, and optimize the structure and quality of the agricultural labor force, which, in turn, will increase agricultural production efficiency.

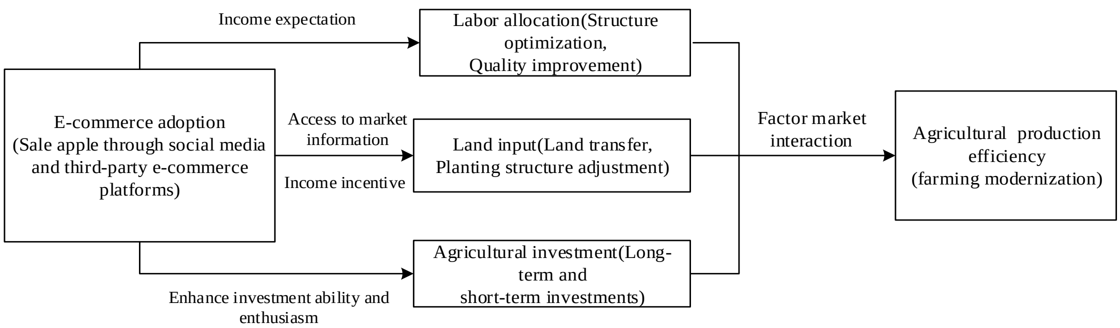

Figure 1. Mechanism through which e-commerce adoption affects agricultural production efficiency.

Second, through e-commerce adoption, land input can be optimized, thus increasing production efficiency in a variety of ways. First, e-commerce adoption can promote land transfer. E-commerce adoption enables farmers to have high expectations for their agricultural income [31], support farmers with comparative advantages in agricultural management to transfer to the land, realize Pareto improvement in land resource allocation, and thereby improve production efficiency. Second, e-commerce adoption promotes the flow of the labor force to rural areas to increase the scale of agricultural operation. The optimization of agricultural labor allocation will increase not only labor productivity, but also the production and allocation efficiency of agricultural land, which will play a positive role in agricultural production efficiency. Third, e-commerce adoption can optimize farmers' planting structure. For example, apples are one kind of high-value agricultural product, e-commerce adoption can increase farmer participation in the market [32], alleviate farmers' information constraints within the agricultural product market, and encourage farmers to produce on demand and reasonably plan their planting structure. Additionally, labor mobility alleviates the shortages of rural labor, reduces the amount that farmers need to engage in part-time employment [33], increases the specialization of apple planting, and optimizes the allocation of land resources, thereby increasing agricultural production efficiency.

Third, e-commerce adoption can stimulate farmer investment in agriculture, thereby improving production efficiency. First, e-commerce adoption can increase income [9], enhance farmers' investment willingness to invest and their investment ability, and encourage farmers to increase agricultural investment in agricultural machinery, organic fertilizer, etc. [34]. Second, e-commerce adoption alleviates the information asymmetry between the production side and the sales side, changes farmers' knowledge structure [35], enables farmers to understand consumers' preferences for characteristic agricultural products in the market so that can produce and process agricultural products according to the actual situation. E-commerce adoption also promotes accurate balances between the supply of and demand from agricultural products, forces farmers to increase agricultural investment in fine farming and change their mode of agricultural production, and adopt new agricultural technology so that they may produce high-quality agricultural products.

Finally, e-commerce adoption promotes the flow of labor and the expansion of operation scale, and encourages farmer investment through resource linkage mechanisms. The capital accumulation through labor force returning to farming increases their investment ability, which urges farmers to increase agricultural investment and improve their use efficiency of agricultural resources such as land [36]. The increase in operation scale encourages agricultural investment. According to the available literature [37], the fragmentation of China's rural areas and the small scale of agricultural land make agricultural production far away from the stage of diminishing marginal returns, which means that rented agricultural land can improve the agricultural land management pattern by optimizing the resource allocation structure. Larger land plots can promote the substitution of capital for labor and stimulate farmers' investment, which can affect the benefit of scale [38].

Notably, the input of organic fertilizer to agricultural land ensures soil fertility and sustainable production. Purchasing agricultural machinery, in the long term, is expensive. Farmer purchase of agricultural technology operation services in the short term is low cost, fast, and low risk [39]. Therefore, we defined farmers' investment in agricultural machinery and organic fertilizer as agricultural long-term investments, and the behavior of farmers purchasing agricultural technology services as agricultural short-term investment, so we could analyze the differences between agricultural long-term investment and short-term investment in the impact of e-commerce participation on agricultural production efficiency. Based on these analyses, we constructed the following hypotheses:

H1. *E-commerce adoption can promote the optimization of agricultural labor allocation and thus positively impacts on agricultural production efficiency.*

H2. *E-commerce adoption can promote the optimization of land input and thus positively impacts on agricultural production efficiency.*

H3. *E-commerce adoption can promote agricultural investment and thus positively impacts agricultural production efficiency.*

3. Methods

3.1. Data Source and Variable Selection

3.1.1. Data Sources

China is the world's largest producer and consumer of apples. As a high-value and labor-intensive agricultural product, apples are not only the dominant industry in some regions, but also a major source of local farmer income. As most of China's areas that are suitable for apple production are far from the markets, smooth sales channels and timely, effective information have a stronger impact on farmers' production decisions. Therefore, taking apple growers as the study object could further reveal the mechanism through which agricultural e-commerce affects agricultural production efficiency. We chose Shaanxi Province as the study area to analyze the development of apple e-commerce and the current adoption of e-commerce by farmers. Our reason for this selection was that Shaanxi is an area suitable for apple production. Both the planted area and apple production of this province rank first within China [40].

We obtained the data used in this study from the Research on the Production and Sales Behavior of Apple Growers conducted by the Apple Industry Economic Research Laboratory of the National Modern Apple Industry Technology System from October to November 2019. We adopted a mixed sampling method, combining probability and scale sampling and simple random. The development, climate, and economic status of apple industry regions we surveyed widely differed in order to more accurately reflect the diversity in the apple industry in China. We conducted in-person surveys with a questionnaire with 840 apple farmers from 14 townships (towns) and 49 administrative villages in 4 counties known for apples, including Baota District, Luochuan County, Huangling County, and Baishui County, Weinan City, Shaanxi Province. We obtained 827 valid surveys after removing invalid surveys, for a questionnaire efficiency of 98.45%.

3.1.2. Variable Selection and Descriptive Statistics

Since we will next compare the characteristic differences between adopters and non-adopters, we first need to give the formula for the t-test. Theoretically, there are differences between adopters and non-adopters in individual characteristics, family characteristics, external environment characteristics, etc. T-test can preliminarily identify these differential variables. We divided the samples into adopters and non-adopters, and we conducted the mean difference test for the two groups of samples. The formula was as follows:

$$diff = mean(x) - mean(y) \tag{1}$$

where *diff* is a proxy variable for the size of the difference, and *mean* refers to the average value of a variable in the sample.

Suppose two samples, X and Y:

$$X \sim N(\mu_1, {\delta_1}^2)\, Y \sim N(\mu_2, {\delta_2}^2) \tag{2}$$

We only know $\rho = \delta_1^2/\delta_1^2$, because:

$$\frac{(\overline{x} + \overline{y} - \mu_1 + \mu_2)\sqrt{mn(n+m-2)}}{\sqrt{(n+m\rho)\left[\frac{1}{\rho}(n-1)S_1^2 + (m-1)S_2^2\right]}} \sim t_{n+m-2} \tag{3}$$

where $\overline{x}$ and $\overline{y}$ represent the averages of samples X and Y, respectively. The variables n and m represent the sample sizes of X and Y, respectively. t_{n+m-2} represents the t-distribution with $n + m - 2$ degrees of freedom. When $\rho = 1$, the above equation can be simplified as:

$$\frac{(\overline{x} + \overline{y} - \mu_1 + \mu_2)\sqrt{mn(n+m-2)}}{\sqrt{(n+m)\left[(n-1)S_1^2 + (m-1)S_2^2\right]}} \sim t_{n+m-2} \tag{4}$$

We used the economic software STATA for this test, and all of the variable characteristics are shown in Table 1. The definitions and statistical characteristics of each variable are shown below. The independent variable was e-commerce adoption. Comprehensively considering the definition in the literature [16,24], we defined e-commerce adoption for agricultural products as farmers' e-commerce behavior through media, social software (WeChat, Jitter, Fast hand, QQ, etc.), and third-party e-commerce platforms (Taobao, Jingdong, spelling Kwai, etc.). When farmers had adopted any of the above e-commerce platforms, we assigned the value of the adoption decision as 1. Otherwise, we assigned a value of 0. Among the sample farmers, 202 participated in e-commerce, accounting for 24.43% of the total. This finding indicated that the development of apple e-commerce was in the initial stage, with a low overall adoption rate.

Table 1. Variable definition and statistical characteristics.

Variable	Definition and Assignment	Adopter	Nonadopter	MD
Agricultural productivity	SFA calculation results	0.383	0.287	0.096 ***
Sex (SEX)	Female = 0; male = 1	0.965	0.959	0.006
Age (AGE)	Age of respondent in 2019/2020 (one full year of life)	53.174	53.630	−0.456 **
Degree of education (EDU)	Education of head of household (years)	8.550	7.752	0.798 ***
Health condition (HEAL)	Very unhealthy = 1; relatively unhealthy = 2; general = 3; relatively healthy = 4; very healthy = 5	4.154	4.012	0.143
Social capital (SOCI)	Number of relatives and friends (persons)	114.14	64.425	49.715 **
Management scale (SCAL)	Hanging apple planting area (acre)	1.671	1.526	0.145 *
Organization participation (ORGA)	Part of cooperative: no = 0; yes = 1;	0.184	0.116	0.068 **
Distance from town (DIST)	Distance to the town (km)	5.471	5.610	−0.139
Disaster situation (DISA)	Whether orchard suffers from natural disasters: no = 0; yes = 1	4.352	4.328	0.024 *
Allocation of labor force	Labor force structure: ratio of agricultural labor force to household labor force (STRU)	0.782	0.615	0.167 *
	Labor force equality: ratio of labor force under 60 years of age to household labor force (EQUA)	0.176	0.200	−0.024 **
Land investment	Land transfer area (acre) (TRAN)	0.361	0.215	0.146 *
	Planting structure adjustment: proportion of apple planting are a (ADJU)	0.878	0.810	0.068 *
Agricultural investment	Long-term agricultural investment: agricultural machinery and organic fertilizer input (USD) (LONG)	5447.58	3612.91	1834.67 **
	Short-term agricultural investment: whether to buy agricultural machinery services: no = 0; yes = 1 (SHOR)	0.119	0.048	0.071 ***

Note: ***, ** and * indicate that mean difference was significant at level of 0.01, 0.05, and 0.1 (T test), respectively.

The dependent variable was agricultural production efficiency. In this study, we used the stochastic frontier production function model (SFA) to estimate agricultural production efficiency. The mean difference between adopters and non-adopters was 0.096, which was significant at the 1% confidence level.

The mediating variable was the allocation of agricultural resources. We mainly analyzed three aspects of agricultural resources: labor force, land, and agricultural investment. We divided the allocation of agricultural resources into labor force, land investment, and agricultural investment. Drawing on previous results [33], we considered the optimization of labor force allocation as reflected by the optimization of labor force structure and labor quality, which we characterized by the proportion of agricultural labor force in the total family labor force and the proportion of labor force under 60 years old in the total family labor force. The optimization of land factor input was reflected in the land transfer and planting structure optimization, which we characterized by the proportion of land transfer to the area and apple planting area, respectively. We divided agricultural investment into long- and short-term investment, represented by agricultural machinery and organic fertilizer input and the purchase of agricultural machinery services, respectively, and took their logarithms. Referring to the literature [6,28], we selected 9 variables as control variables, including the household owner's personal characteristics (sex, age, education level, and health status), family characteristics (social capital), production characteristics (orchard area), organizational characteristics (cooperative participation), transportation characteristics (distance from the nearest township), and natural disaster situation.

3.2. Research Methods

3.2.1. Stochastic Frontier Analysis Method (SFA)

The methods of measuring agricultural production efficiency can be roughly divided into two categories. The first is parametric analysis, represented by the stochastic frontier production function (SFA). The second method is nonparametric analysis, represented by data envelopment analysis (DEA). As random factors, such as precipitation, temperature, and light, importantly impact the output of agricultural products, efficiency analysis using DEA is prone to errors [41–43]. In this study, we selected a more suitable stochastic frontier production function model to estimate the technical efficiency, and the model form is as follows:

$$LNg_{it} = LNf(x_{it}, \beta) + v_{it} - u_{it} \tag{5}$$

where g_{it} and $f(x_{it},\ \beta)$ represent the actual output of the ith farmer in period t and the optimal output level under the given input, respectively. x_{it} is the inputs of the ith farmer in period t. β is the parameter to be estimated. v_{it} is a random disturbance term that obeys normal distribution. u_{it} is the technical inefficiency item, reflecting the distance between the ith farmer and the efficiency frontier in period t.

The specified production function is denoted by f (•). The commonly used production functions include the C-D and trans logarithmic production functions. Although the C-D production function is simple and easy to estimate, the assumption of the constant elasticity of factor substitution is inconsistent with actual agricultural production. Therefore, we chose the trans logarithmic production function, which is more inclusive and flexible. According to the literature, we set the production function from the perspective of land output value. The main input factors included capital, labor, and land [44] and the specific form of the function was as follows:

$$\begin{aligned} LnG_i = \beta_0 + \beta_1 LnLF + \beta_2 LnL + \beta_3 LnC + \beta_{12} LnLFLnL + \beta_{13} LnLFLnC \\ + \beta_{23} LnLLnC + 0.5\beta_{11}(LnX_1)^2 + 0.5\beta_{22}(LnL)^2 + 0.5\beta_{33}(LnC)^2 + v_i - u_{it} \end{aligned} \tag{6}$$

where G_i represents apple output. LF, L and C represent the inputs of labor, land and capital input, respectively, including fertilizer and so on. β is the parameter to be estimated. v_i is the random interference term.

We used the maximum likelihood method (MLE) to estimate Equation (5). Then, the production technical efficiency of the farmer in the period could be expressed as:

$$TE_{it} = \frac{g_{it}}{\exp[f(x_{it}, \beta) + v_{it}]} \tag{7}$$

3.2.2. Propensity Score Matching (PSM)

Apple growers' participation in e-commerce is a "self-selection" process and their choice may be affected by their own capital endowment, that is, farmers were not randomly e-commerce users or not, and the factors that affected their choice would impact their production efficiency. Therefore, ignoring the self-selection problem will lead to biased parameter estimation results.

Propensity score matching (PSM) is a method commonly used to deal with the sample self-selection problem. We used the PSM method to deal with the self-selection problem in e-commerce adoption, that is, based on the sample of non-e-commerce farmers, we matched a non-e-commerce farmer to each e-commerce farmer, so that the characteristics of the two farmers were approximately the same except for the differences in e-commerce adoption behavior. Therefore, the variables of the two sample individuals could be regarded as the results of two different experiments (adopting e-commerce or not) conducted by the same farmer, and the difference in the variable was the net effect of e-commerce adoption. For the whole e-commerce farmers group, we called this net effect the average processing effect (ATT). Specifically, the matching score of apple farmers' propensity to participate in e-commerce was the probability of their participation in e-commerce under given conditions. We used the logit model or probit model to estimate the matching score of apple farmers' propensity to participate in e-commerce. Taking the logit model as an example, its expression is:

$$P(Z_i) = P(D_i = 1|Z_i) = \exp(\hat{Z_i}\alpha)/(1 + \exp(\hat{Z_i}\alpha)) \tag{8}$$

where $P(D_i = 1|Z_i)$ is the matching score or probability of apple growers' tendency to participate in e-commerce, and Z_i is the matching variable.

After we obtained the propensity matching score, we selected an appropriate matching method to match adopters and non-adopters. The commonly used matching methods include nearest neighbor matching, core matching, radius matching, etc. After the matching was completed, we measured the impact of e-commerce participation on the production efficiency of apple growers. We used the average processing effect of agricultural production efficiency of the processing group (i.e., the adoptions) to estimate, and the expression is as follows:

$$ATT = E(Y_1|D = 1) - E(Y_0|D = 1) = E(Y_1 - Y_0|D = 1) \tag{9}$$

where Y_1 is the agricultural production efficiency of farmers after adopting e-commerce. Y_0 is the agricultural production efficiency of farmers not adopting e-commerce. Only the result of $E(Y_1 \mid D = 1)$ could be observed, and the result of $E(Y_0 \mid D = 1)$ could not. We used the PSM method to construct the substitute index.

4. Results

4.1. Estimation of E-Commerce Adoption Decision Equation of Apple Farmers

The following results show that we found significant differences between adopters and non-adopters in terms of age, education level, social capital, orchard area, and transportation convenience. Table 2 provides the equation regression results of the e-commerce adoption decision of apple farmers that we estimated based on a logit model. Our results suggest that the age of respondents positively impacted farmers' e-commerce adoption significant at a confidence level of 10%. The impact on e-commerce adoption showed an inverted U structure, that is, within a certain range, the likelihood of e-commerce adoption increased with increasing age, but beyond this critical value, the likelihood of e-commerce adoption decreased with increasing age. This may be caused by these reasons that relatively young farmers are less dependent on agriculture and have less enthusiasm to adopt e-commerce, but the increase in age, farmers' dependence on agriculture increases and their subjective motivation to adopt e-commerce is stronger, which encourages them to increase their income through e-commerce apple sales. However, beyond a certain age range, farmers' Internet skills begin to drop and the ability to adopt e-commerce reduces.

Our results suggest that education level positively impacted farmers' e-commerce adoption at the 1% significance level, the possible reason may be that more educated farmers had a deeper understanding of and stronger ability to perform agricultural e-commerce, so they were more likely to adopt e-commerce. Social capital positively impacted farmers' e-commerce adoption at the 1% significance level, we can interpret that as rural China is an acquaintance society, and rural residents exist within a highly intertwined human relationship network. They very frequently deal with people that they know through kinship, friendship, and geographical and industrial relationships, which leads to rapid information dissemination. Therefore, farmers with rich social capital could obtain more information and technical support regarding agricultural e-commerce, so they were more likely to adopt e-commerce. The results show that the planting area positively impacted farmers' adoption decision at the 5% significance level, which may have been because farmers with larger businesses had more realistic demand and motivation to expand sales and were more enthusiastic regarding the adoption of agricultural e-commerce.

Table 2. Estimated results of e-commerce adoption decision of apple growers based on Logit model.

Variable	Coefficient	SD
GEN	0.077	0.258
AGE	0.080 *	0.041
AGES	−0.001 *	0.001
EDU	0.089 ***	0.017
HEAL	0.133	0.089
SOCI	0.004 ***	0.001
SCAL	0.011 **	0.004
ORGA	0.014	0.010
DIST	−0.033 **	0.014
DISA	−0.043	0.266
LR	57.62 ***	
Pseudo R^2	0.0837	
Log likelihood	−312.90285	
Observation number	827	

Note: ***, ** and * indicate that the mean difference is significant at the confidence level of 0.01, 0.05 and 0.1.

The results show that the distance from villages and towns negatively impacted farmers' adoption of agricultural e-commerce and this impact was significant. The reason for this may be that the development of agricultural e-commerce depends on the improvement in infrastructure such as logistics and the Internet, especially for rural areas in mountainous and hilly areas. Farmers closer to a township center have a better logistics and Internet connections, which can effectively reduce the transaction cost of farmers' adoption of agricultural e-commerce, which facilitate adoption into practice.

4.1.1. Common Support Domain

Before and after matching, the propensity score interval of the experimental and control groups overlap to a certain extent, which is called the "common support domain". The larger the range of the common support domain in the matching process, the less the sample size is lost. To more intuitively show the common support areas of farmers who adopted e-commerce and those who did not, Figure 2 shows the probability density diagrams of the propensity scores of the preprocessing and control groups before and after matching. Figure 3 depicts the propensity score after matching. The kernel density function of the propensity score of the two groups after matching was relatively close, and the matching effect was better.

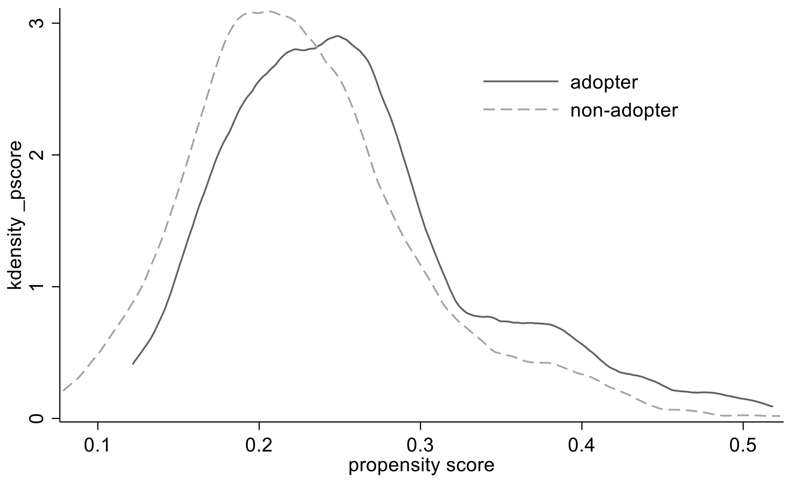

Figure 2. The propensity score of adopters and non-adopters before matching.

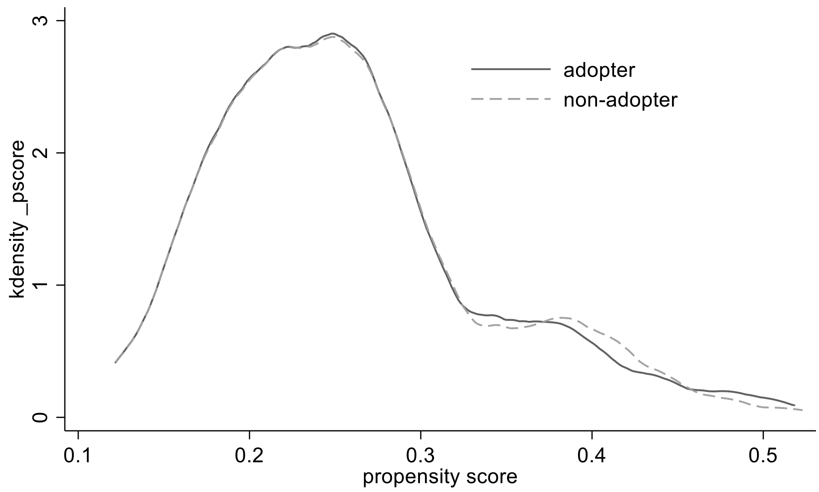

Figure 3. The propensity score of adopters and non-adopters after matching.

4.1.2. Balance Test

To ensure the robustness of the results and effectively use the farmer samples, we adopted four matching methods: nearest neighbor matching (1–3 matching), nearest neighbor matching (1–5 matching), kernel matching (bandwidth 0.06), and kernel matching (bandwidth 0.1). The results showed that the sample loss of the above matching methods was small, indicating that the samples were well-matched. Table 3 reports the standardized deviation of the variables before and after matching. After matching, the standardized deviation of all variables decreased, and the standard deviation of all explanatory variables was within 10%. The pseudo R^2 decreased from 0.081 before matching to 0 to 0.004 after matching. The LR statistics decreased from 91.26 before matching to 6.29 to 9.15 after matching. The joint significance of explanatory variables changed from highly significant before matching to high probability of rejection, and the mean deviation of explanatory variables decreased from 11.09% before matching to 1.2% to 3.7% after matching. The median deviation decreased from 21.10% before matching to 1.2% to 3.1%, so the total bias decreased. The above results showed that the propensity score estimation and sample matching were successful, and the matching results met the balance requirements.

Table 3. Balance test results of explanatory variables before and after matching.

Matching Method	Pseudo R^2	LR Value	p Value	Mean Deviation (%)	Median Deviation (%)
Before matching	0.081	91.26	0.005	11.09	21.10
Neighbor matching (1 to 3 matching)	0.000	9.08	1.000	1.20	1.20
Neighbor matching (1 to 5 matching)	0.000	6.29	1.000	1.20	1.30
Kernel matching (bandwidth 0.06)	0.003	8.37	0.998	2.10	1.70
Kernel matching (bandwidth 0.1)	0.004	9.15	0.911	3.70	3.10

4.2. PSM Estimation Results of Effect of Farmers' E-Commerce Adoption on Agricultural Productivity

Table 4 reports the agricultural productivity and ATT values of the experimental and control groups obtained with the four matching methods. The results of the four matching methods were basically consistent. ATT passed the test at the 1% significance level, which showed that the estimation results were robust. From the mean value, if farmers did not adopt e-commerce, their agricultural production efficiency was 0.302. After adopting e-commerce, their agricultural productivity was 0.376, which is a significant increase by

0.074. This finding showed that e-commerce adoption can significantly improve farmers' production efficiency.

Table 4. Estimated results of the impact of farmers' adoption of e-commerce on agricultural production efficiency.

Matching Method	Experimental Group	Control Group	ATT	SE	T Value
Neighbor matching (1 to 3 matching)	0.376	0.296	0.080	0.022	3.64
Neighbor matching (1 to 5 matching)	0.376	0.304	0.072	0.021	3.43
Kernel matching (bandwidth 0.06)	0.376	0.306	0.070	0.019	3.68
Kernel matching (bandwidth 0.1)	0.376	0.303	0.073	0.021	3.48
Mean	0.376	0.302	0.074	0.021	3.56

Note: Only individuals within the common value range are matched.

Endogenous Problems

Although PSM solves the problem observable selectivity bias, it may still have endogenous problems. The three causes of endogenous problems are: first, missing variables, although we fully considered individual, family, production, and external environment characteristics in the selection of control variables in this study, agricultural productivity could have also been affected by some unobservable variables. The second cause is two-way causality. Farmers' e-commerce adoption could promote the increase in agricultural productivity, and the increase in efficiency may have also stimulated farmers' enthusiasm to adopt agricultural e-commerce, so e-commerce adoption would have been related to random disturbance items, resulting in deviation in the empirical results. To overcome the endogenous problem of variables, we selected "How many of the 10 people you interact with regularly adopt e-commerce?" as a tool variable to test. The reason is that China's rural areas are typical of "acquaintance society" and farmers are easily influenced by others in psychology and behavior. The adoption of e-commerce by people around them will prompt farmers to make adoption decisions, but will not affect agricultural productivity directly, which meets the correlation and exogenous conditions of instrumental variables. The estimation results of the Tobit model based on the instrumental variables are shown in Table 5. The Durbin-Wu-Hausman test results showed that the Wald chi-square test rejected the original assumption that e-commerce was adopted as exogenous at the 1% significance level, indicating that the model was endogenous. The F statistic in the weak instrumental variable test was 19.20, which is greater than the critical value of 16.38 at the 10% bias level, indicating that the instrumental variable was effective. The estimation results showed that the impact of e-commerce adoption on agricultural productivity was consistent with the PSM results, which effectively supports the above PSM results.

Table 5. Estimation results of instrumental variable method.

	Tobit Model 1	IV-Tobit Model 2
E-commerce adoption	0.301 *** (0.091)	0.233 *** (0.061)
Control variables	Controlled	Controlled
Log likelihood	418.52452	
Pseudo R^2	0.0812	
Wald test		2.81 *
F value in the first phase		19.20 ***
R^2		0.1609
Adjusted R^2		0.1524
Observation number	827	827

Note: *** and * indicate that the mean difference is significant at the confidence level of 0.01 and 0.1. The values in brackets are standard deviations.

4.3. Mechanism Test of Farmers' E-Commerce Adoption Affecting Agricultural Productivity

The results show that we found ae significant differences in agricultural resource allocation between adopters and non-adopters.

Models 3 and 4 in Table 6 show that e-commerce adoption had optimized the structure and quality of the agricultural labor force. The reason may be that as a knowledge-intensive sales method integrating modern Internet technology, agricultural e-commerce requires higher cultural and technical skills, which force agricultural practitioners to improve their own skills. Farmers have high income expectations with e-commerce adoption, which is driving the transfer of labor force from nonagricultural to agricultural employment. Agricultural e-commerce is knowledge-intensive, which requires farmers to have strong skills in using Internet. However, the elderly labor force may not have these skills, thereby force the agricultural work force to improve their own skills. Hypothesis 1 was supported.

Table 6. Results of the impact of e-commerce adoption on agricultural factor allocation.

	STRU Model 3	QUAL Model 4	TRAN Model 5	ADJU Model 6	LONG Model 7	SHOR Model 8
E-commerce participation	0.300 *** (0.012)	−0.418 ** (0.016)	0.104 *** (0.120)	0.200 ** (0.109)	0.978 *** (0.276)	0.187 *** (0.286)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Wald test	2.97 *	2.88 *	3.21 *	3.13 *	6.21 **	3.27 *
F value in the first phase	15.25 ***	13.33 ***	15.15 ***	13.52 ***	16.31 ***	12.85 ***
R^2	0.1409	0.1404	0.1145	0.1102	0.1387	0.1144
Adjusted R^2	0.1272	0.1299	0.1070	0.1091	0.1302	0.1055
Observation number	827	827	827	827	827	827

Note: ***, ** and * indicate that the mean difference is significant at the confidence level of 0.01, 0.05 and 0.1. The values in brackets are standard deviations.

According to Models 5 and 6, e-commerce adoption encouraged farmers to transfer to land, optimize their planting structure, and increase the proportion of apples in their planted area. This may be caused by these reasons, as a perennial high-value agricultural product, e-commerce could effectively encourage farmers to move to rural areas and to adjust their planting structure in order to maximize their income. Hypothesis 2 was supported.

According to Models 7 and 8, e-commerce adoption significantly promoted long-term agricultural investment such as the purchase of agricultural machinery and the use of organic fertilizer, as well as short-term investments such as agricultural technology purchase and service. The reason may be that e-commerce adoption enabled farmers to have higher investment and resource allocation abilities, and encouraged farmers to buy more fixed investments such as agricultural machinery and organic fertilizer and short-term investments such as agricultural services. Hypothesis 3 was supported.

5. Discussion

5.1. Comparison with Previous Results

Some meaningful conclusions have been drawn about the impact of farmers' participation in e-commerce. For example, the results of a study of reservoir relocators showed that participation in e-commerce significantly promoted the adoption of green production technologies by farmers, and that expectations of the ecological value of agricultural products and the agricultural technical support provided by e-commerce were important driving factors [45]. The development of rural e-commerce has become the most important method to promote agricultural modernization, implement the rural revitalization strategy in the new era, and realize green innovation and the sustainable development of regional economies [46,47]. E-commerce participation has a significant positive effect on farmer income [48]. However, few researchers had selected apple growers as their object of study.

People's consumption concepts have considerably changed. They are increasingly concerned about health and the demand for improving the ecological environment is gradually strengthening. The role of apples in improving human nutrition and the environment is paramount. Compared to previous studies, we showcase a micro-economic demonstration of farmers' e-commerce participation in the apple industry. We found that apple growers can improve production efficiency by improving resource allocation.

5.2. Research Implications

As mentioned above, apple farmers' participation in e-commerce can substantially improve their productivity. Participation in e-commerce can also improve sustainable development and reduce environmental impacts by reducing inputs that pollute the environment and by providing farmers with more information on such inputs so they can make better purchasing decisions. In the past, increases in agricultural productivity mainly depended on the input of large amounts of fertilizers and pesticides, which negatively impact the environment [49,50]. Now, e-commerce participation can help farmers to more effectively allocate land, labor, capital, and other resources, so that farmers are less dependent on fertilizers and pesticides thereby using less. Also, because the e-commerce of agricultural products will more effectively provide market information, products with high fertilizer and pesticide contents and applications will be less popular, so farmers will reduce their use.

E-commerce can also improve community relationships. Apple farming is a labor- and technology-intensive agricultural product, with relatively concentrated production and sales links. Farmers often need to hire workers, but the difficulty of hiring workers has long been a problem in apple-producing areas [51]. The wages of hired workers are high, and finding people with spare time is difficult. Higher agricultural productivity means that farmers have more incentive to grow apples, which raises their price expectations for workers, and they hire more local people. At present, farmers mainly rely on mobile phones to participate in e-commerce. The increasing use of mobile phones reduces the transaction cost of employees needed, so that they can find part-time labor more easily. In addition, increases in productivity makes farmers more efficient in the production and marketing seasons. As such, more people will help their relatives or friends on the farm after working on their own farm. Therefore, the interactions between people will increase, which will improve the good relationships between the communities and create a harmonious community atmosphere.

6. Conclusions and Recommendations

Taking 827 apple farmers in Shaanxi Province as our sample, we used the random frontier production function (SFA) and propensity score matching (PSM) to calculate the production efficiency and analyze the average treatment effect of e-commerce adoption on farmers' production efficiency. We discussed the path through which e-commerce adoption improves farmers' production efficiency. The results showed that, first, e-commerce adoption can significantly improve farmers' production efficiency, and the production efficiency of farmers who adopted e-commerce was 24.5%, which was higher than that of farmers who did not adopt e-commerce. This finding indicated that e-commerce adoption can force farmers to improve production efficiency, which is an important force driving increases in agricultural production efficiency in the new era. Second, e-commerce adoption had a positive impact on agricultural production efficiency by optimizing agricultural resource allocation. Among them, the contribution rate of agricultural resource allocation was land transfer, agricultural labor quality optimization, agricultural labor structure optimization, long-term agricultural investment, short-term agricultural investment, and planting structure optimization. With this study, we expanded the research on the economic effect of rural e-commerce adoption, and we provided theoretical and empirical evidence for promoting agricultural transformation and upgrading and accelerating agricultural modernization. Based on the above analysis, we provide three policy recommendations.

First, government departments should pay attention to the development of rural e-commerce and promote its popularization through multiple channels. Infrastructure such as the Internet, transportation and logistics in rural areas should be constructed and improved; e-commerce demonstration parks should be set up. The effective supply of public goods and services needs to be ensured, and agricultural e-commerce should be publicized through the Internet, radio, television, and brochures. E-commerce training for farmers needs to be strengthened, and the constraints affecting farmers' adoption of e-commerce in terms of information technology need to be overcome, eliminating the practical obstacles to farmers' adoption, thereby increasing e-commerce adoption, so as to enable farmers to benefit from e-commerce adoption.

Second, government departments should formulate relevant policies to promote farmers' rational allocation of agricultural production resources and improve allocation efficiency. In terms of the labor force, farmers should be guided to reasonably allocate their family labor force, improve the use rate of labor resources, promote labor force mobility, and pay attention to the training of the agricultural labor force in agricultural technology to improve the quality of the labor force. In terms of land, the government should revitalize the rural cultivated land resources, standardize the land transfer mechanism, reduce the transaction cost of land transfer, and promote the appropriate management of the scale of land. In terms of capital, the government should guide farmers to improve capital use, provide financial subsidies and low-interest loans for agricultural investment, and improve farmers' investment enthusiasm.

Third, government departments should actively introduce agricultural science and technology based on the Internet. Governments at all levels should cooperate with scientific research institutions, farmers' professional cooperatives, and enterprise associations to strengthen agricultural science and technology innovation, comprehensively consider external environmental factors and the heterogeneity of individual farmers, establish science and technology promotion mechanisms with diversified channels and forms, introduce modern digital technology on the basis of traditional agricultural elements, and promote the optimization and transformation of the production mode, thereby improving the efficiency of agricultural resource allocation and realizing the sustainable development of the rural economy.

This paper shows the influence mechanism of e-commerce participation on agricultural production efficiency, and expands research about the influence of e-commerce on agriculture, environment, and communities development, but there is still room for improvement. In the future, scholars can explore the heterogeneity of the influence of different e-commerce modes on agricultural production efficiency, and make comparison, so as to put forward more meaningful suggestions for the promotion of e-commerce. In addition, future studies can expand the research area of micro farmers to reach a more common conclusion.

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