agriculture

Article

Will the Adoption of Early Fertigation Techniques Hinder Famers' Technology Renewal? Evidence from Fresh Growers in Shaanxi, China

Jiahong Yuan, Xiaoyu Li, Zilai Sun and Junhu Ruan *

College of Economics and Management, Northwest A&F University, Yangling 712100, China; yjh51251@nwafu.edu.cn (J.Y.); lxy2018910@nwafu.edu.cn (X.L.); drszl@nwafu.edu.cn (Z.S.)
* Correspondence: rjh@nwsuaf.edu.cn; Tel.: +86-185-0292-4249

Abstract: Fertigation technology is key to solve water pollution and inefficient fertilizer use. However, some early techniques cannot adapt to the current situation of labor shortages and large-scale planting. Therefore, it is necessary to consider farmers' willingness to adopt more adaptive techniques. Specifically, we focus on whether early technology adoption will hinder technology renewal and whether the factors affecting the adoption of early and latest techniques are consistent. Through theoretical analysis and a survey, we find that farmers' endowments such as income and labor force only affect the adoption intentions to the high-cost technique (Intelligent Irrigation Control System), but not early techniques (Venturi injector and Differential pressure tank), while farmers' information processing ability and information acquisition channels affect both. Finally, the results of Propensity Score Matching show that early technology adoption will not become an obstacle to technology renewal.

Keywords: fertigation; technology adoption; intelligent irrigation control system; farmer's endowments; technology understanding

Citation: Yuan, J.; Li, X.; Sun, Z.; Ruan, J. Will the Adoption of Early Fertigation Techniques Hinder Famers' Technology Renewal? Evidence from Fresh Growers in Shaanxi, China. *Agriculture* **2021**, *11*, 913. https://doi.org/10.3390/agriculture11100913

Academic Editor: Johannes Sauer

Received: 30 July 2021
Accepted: 22 September 2021
Published: 24 September 2021

1. Introduction

The inefficient use of chemical fertilizer has always been a major cause of agricultural environmental pollution [1,2], and fertigation is regarded as an effective solution [2]. According to Fan et al. [3], fertigation can keep the output unchanged, while saving 30–50% fertilizers and 50% water. Because of its significant advantages, some farmers have adopted simple fertigation techniques, such as the Venturi injector. However, for various reasons, these techniques have not been fully popularized [4].

In recent years, with the advancement of urbanization and land marketization, labor shortages and large-scale planting have become new characteristics of China's agriculture [4–6]. Early fertigation techniques are not well adapted to these characteristics because of their small applicable area, artificial errors, and labor demand [7]. Lu and Xie found that a labor shortage can exacerbate agricultural non-point source pollution caused by chemical fertilizer [5]. Additionally, a larger planting scale requires more efficient and labor-saving agricultural technologies [8]. Therefore, with as advantages its labor-saving characteristics and large-scale application, the Intelligent Irrigation Control System (IICS) has become a possible solution [9]. In view of China's support for digital agriculture and the development of IICS, how to improve the adoption of it is an important topic [10].

Because of the inconsistency of the adoption of fertigation technologies among farmers, relevant studies have widely investigated the role of farmers' heterogeneity. For example, Yang et al. found that high-income and young farmers have higher adoption rates of fertigation techniques [11], and credit markets and subsidies can weaken these effects [12]. The lack of understanding and application ability of technology also hinders farmers' adoption [13]. In addition, age, gender, education, and other demographic characteristics also affect the adoption of fertigation techniques [14,15]. At present, with the enrichment of relevant research, factors have expanded to psychological factors, such as environmental attitude [1,16,17]. In general, regardless of the factors studied, most of the current research focuses on linear technology renewal, that is, in all papers, farmers are at the same technical level before adopting the new technology.

However, an easily overlooked problem is whether farmers are really at the same initial technical level. In China and other countries with slow agricultural development, due to the rapid renewal of technology, there may be intergenerational differences in the technologies currently adopted by farmers [18]. Not all farmers have adopted the early fertigation techniques. Those farmers who adopt these techniques have paid "sunk costs", which may reduce their expected benefits of adopting the latest technology. This will lead to the possibility that the government needs to specifically subsidize these farmers.

In addition, because the policies required for different technologies may be different, and there is policy conversion cost, some scholars have studied the role of farmers' heterogeneity in different technologies [19]. However, there are great differences in the technologies they have studied. For example, Mao et al. [20] studied how farmers make decisions when facing multiple green production technologies. Moreover, while, according to the definition of Garcia and Calantone, even compared to earlier technologies, IICS has a higher cost and less labor demand, it still belongs to the same kind of technology, named continuous innovations [21,22]. The comparative analysis of these technologies needs to be further explored. This will help governments determine whether to retain the original policies or develop new policies. Therefore, this paper focuses on two questions: (1) whether the factors affecting farmers' adoption of these two types of techniques are the same; (2) whether the adoption of early techniques will affect farmers' adoption of IICS.

There are limitless factors affecting farmers' adoption, and it is impossible to investigate them all. Therefore, we divide the factors into two categories according to different research priorities and some review researches [23]. Some scholars believe that the cognitive differences between farmers and experts on technology will affect the adoption [24–27]. They believe that the lack of knowledge and skills is a major obstacle to the adoption of this technology, and information dissemination and training are key [26]. For example, Nakano et al. found that the adoption rate increased after training, and untrained farmers also gradually learned from the adopted farmers [27]. We classify these factors as farmers' understanding, reflecting the gap between farmers' and technology developers' understanding and use of technology. Factors such as education, age, location in social networks, and connections with agro-promoters have been proved to have significant impacts on farmers' understanding of technology, thus affecting farmers' intentions [28].

Other scholars emphasize the importance of cost–benefit [29,30]. Due to the heterogeneity of farmers, the benefits of adopting the same technology are also different [29]. This kind of factor is farmers' endowment, which determines whether the technology is suitable for the specific farmer, and ultimately affects their adoption intentions [17]. We will not consider other factors, such as environmental attitudes [1], as the two types of techniques are similar.

Takahashi et al. [31] indicated that whether technology can bring about significant revenue growth is the first thing to consider. Therefore, based on the previous research [32,33], we establish a theoretical model to analyze the expected benefits of two types of technology adoption. We first consider the impact of factor endowment under complete information. Then, regarding famers' understanding as a coefficient, we multiplied the returns to determine the expected benefit [32,33]. Moreover, we discuss the impact of adopting early technologies. Empirically, we used the data of vegetable farmers in Shaanxi Province, China to verify our analysis. Furthermore, we use Logit Regression and Propensity Score Matching (PSM) to analyze the two questions we proposed above.

The rest of this article is structured as follows. We first propose a theoretical model of adoption intentions subject to famers' understanding and factor endowments in Section 2. Then, we describe the data and methods used in Section 3. Furthermore, we present the main results and findings by the ordinal logistic regression and PSM in Section 4. In Section 5, we discuss the results and sum up our work.

2. Model and Deduction

This section aims to answer the above two questions from a theoretical level. As mentioned above, because the techniques belong to continuous innovation, the action mechanism of farmers' heterogeneity is relatively similar, which needs to be quantified to compare their differences. Referring to the existing research [32,33], which states that farmers' behavior depends on the comparison of benefits before and after technology adoption, we quantified the differences with the help of economic models. We used an expected benefit model to compare the income difference between three types of technologies, i.e., surface fertilization, early fertigation techniques, and IICS, and put forward our hypothesis.

2.1. Investment Return Curve of Technology Adoption

Firstly, to simplify the model, we transformed the return on technology adoption into a marginal return curve varying with input, which will help us discuss the role of endowments and credit markets below. For any technology f, the benefits of adopting it H are:

$$H = pf(K, L, m) - cm \tag{1}$$

where p denotes the price of products, m denotes the land scale, c denotes the input per unit of land, K and L represent the capital and labor input, respectively, and $cm = K + \omega L$, where ω reflects the price of labor. In this work, we ignore the fixed costs because fixed investment is generally provided by local governments, which will complicate the model. In addition, some other studies have also ignored them [32,33].

Frist, under the condition of constant return to scale, we can get:

$$h = pf(k, l) - c \tag{2}$$

where lower case letters h, k, and l indicate the profit, required labor, and capital per unit, respectively. For each fixed c ($c = \omega l + k$), the goal of profit maximization can be expressed as:

$$\max_{l,k} f(k, l), \;\; s.t. c = \omega l + k \tag{3}$$

This means that for a typical concave and continuous production function, under a given total input c, there exists an optimal input ratio of capital and labor to maximize output. Therefore, the goal of profit maximization under variable input is:

$$\max_{c} (pf(c) - c). \tag{4}$$

h can be expressed as:

$$h = pf(c) - c \tag{5}$$

We used r to express the yield, and the corresponding marginal profit rate curves are:

$$r(c) = \frac{\partial pf(c)}{\partial c} - 1 \tag{6}$$

As shown in Figure 1, due to the decreasing marginal return, the marginal profit margin curve may arise in the initial stage, and then generally decline. This means that with the continuous increase of investment, even if the capital labor-input ratio is optimal, the marginal rate of return will still gradually decline. Agricultural production is usually located in the area where the marginal rate of return decreases. Therefore, the adoption of new techniques can be regarded as an investment behavior, and farmers are facing an income curve with a declining marginal return. This part is similar to the introduction of the marginal return curve in economics textbooks [34].

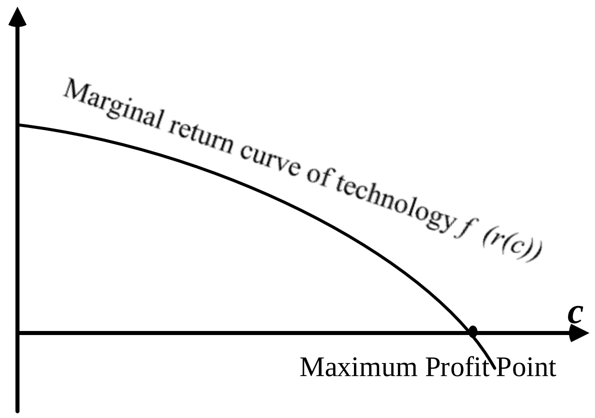

Figure 1. Marginal return curve of technology f.

2.2. The Role of Borrowed Funds

When farmers invest only with their own labor and capital, for their different endowments, their marginal rates of return are not equal. This is consistent with those studies that do not consider the role of credit markets [11]. However, as Magruder [12] pointed out, credit markets can reduce the impact of capital constraints. When farmers can borrow funds to adopt, their marginal return must be equal to the use cost of funds. We assume that the initial endowment is e_0, the deposit interest rate is i_d, and the loan interest rate is i_l.

For surface fertilization f_1, where farmers do not need to borrow funds, the investment c_1^* and corresponding profit h_1 are:

$$r_1(c_1^*) = \frac{\partial p f_1(c_1^*)}{\partial c_1^*} - 1 = i_d,\ h_1 = p f_1(c_1^*) - c_1^* + (e_0 - c_1^*) i_d \tag{7}$$

For early fertigation techniques f_2, where farmers do not need to borrow funds ($e_0 > c_2^*$), the investment c_2^* and corresponding profit h_2 are:

$$r_2(c_2^*) = \frac{\partial p f_2(c_2{}^*)}{\partial c_2{}^*} - 1 = i_d,\ h_2 = p f_2(c_2^*) - c_2^* + (e_0 - c_2^*) i_d \tag{8}$$

The profit difference before and after the adoption of early fertigation techniques is:

$$\Delta h = h_2 - h_1 = p[f_2(c_2^*) - f_1(c_1^*)] + (c_1^* - c_2^*)(1 + i_d) \tag{9}$$

We can see that in Equation (9), is offset; moreover, farmers' endowments will not affect the profit difference. As shown in Figure 2a, when $e_0 > c_2^*$, no matter how e_0 increases, the adoption income remains unchanged. However, for IICS, f_2', where farmers need to borrow funds ($e_0 < c_2^{*\prime}$), the investment $c_2^{*\prime}$ and corresponding profit h_2' are:

$$r_2(c_2^{*\prime}) = \frac{\partial p\ f_2'(\ c_2^{*\prime})}{\partial\ c_2^{*\prime}} - 1 = i_l, h_2' = p\ f_2'(c_2^{*\prime}) - c_2^{*\prime} + (e_0 - c_2^{*\prime}) i_l \tag{10}$$

The profit difference before and after the adoption is:

$$\Delta h' = p\left[f_2'(c_2^{*\prime}) - f_1(c_1{}^*)\right] + c_1{}^*(1 + i_d) - c_2^{*\prime}(1 + i_l) + e_0(i_l - i_d) \tag{11}$$

We can see that in Equation (11), because of the interest rate spread, e_0 is not offset. As shown in Figure 2b, when $e_0 < c_2^{*\prime}$, the change of e_0 will lead to the change of shadow A. This shows that the role of farmers' endowment depends on the adoption cost of technology. When farmers need to borrow funds to adopt technology, due to the high loan cost, farmers' expected income will decline. The extent of decline depends on the number of access funds and ultimately on the endowment of farmers. Magruder [12] and Wossen et al. [35] believe that credit constraints can only reduce the role of capital constraints, not completely eliminate it, which is consistent with our research on the adoption of high-cost technology. Based on the above analysis, we obtain the first deduction.

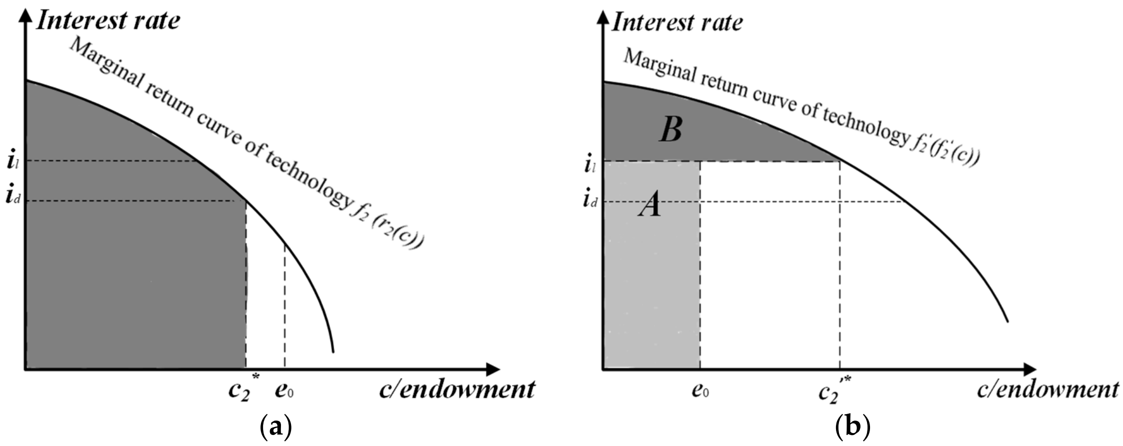

Figure 2. Changes of farmers' adoption income with technology adoption cost: (**a**) Income of low-cost technology adoption; (**b**) Income of high-cost technology adoption. The shaded part A represents the income affected by farmers' endowment (e_0), while the shaded part B represents the constant income. c_2^* and $c_2^{*\prime}$ are the corresponding optimal investment.

Deduction 1. *Farmers' endowments only affect the adoption of high-cost technologies, but not the adoption of low-cost technologies.*

2.3. The Role of Famers' Understanding

The implicit assumption of the above analysis is that farmers fully understand the two technologies, so they can make optimal production decisions. In reality, the impact of farmers' perception of technology must be considered. Here, we assume that farmers fully understand surface fertilization (f_1), but not the new techniques (f_2 and f_2'). Referring to the existing research [33], "$pg(m)\tilde{e} - (w+r)m \geq pf(m) - rm$", we use the $\tilde{e}$ to express farmers' understanding.

Therefore, the expected benefits of farmers' adoption are as follows:

$$E(h_2) = \tilde{e}[pf_2(c_2^*) - c_2^*(1+i_d)] + e_0 i_d \tag{12}$$

and:

$$E\left(h_2'\right) = \tilde{e}\left[pf_2'\left(c_2^{*\prime}\right) - c_2^{*\prime}(1+i_l)\right] + e_0 i_l \tag{13}$$

The expected profit difference before and after adoption is:

$$E(\Delta h) = \tilde{e}[pf_2(c_2^*) - c_2^*(1+i_d)] + c_1^* + c_1^* i_d - pf_1(c_1^*) \tag{14}$$

or:

$$E\left(\Delta h'\right) = \tilde{e}\left[pf_2'\left(c_2^{*\prime}\right) - c_2^{*\prime}(1+i_l)\right] + c_1^* + c_1^* i_d - pf_1(c_1^*) + e_0(i_l - i_d) \tag{15}$$

We can see that in Equations (14) and (15), regardless of the cost, farmers' understanding still has an impact on the expected income, and then affects the willingness of technology adoption. This is consistent with the research of Suvedi et al. [13] and Nakano et al. [27], who showed that richer information channels and higher information processing capacity can improve farmers' willingness to adopt. Thus, we obtain the second deduction.

Deduction 2. *Farmers' understanding of technology always affects their adoption of different cost technologies.*

2.4. Impact of Early Technology Adoption

Here, we consider a common situation. An early low-cost technology f_2 ($e_0 > c_2^*$), different from surface fertilization (f_1), has been adopted by some farmers, and new high-cost technology, f_2' ($e_0 < c_2^{*\prime}$), has matured.

The expected benefits of farmers who have adopted early techniques to update technology are represented by $h_2' - h_2$, while for those who have not adopted, the expected benefits are represented by $h_2' - h_1$. Therefore, the expected profit difference between farmers who adopt early techniques and those not, $E(\Delta h'')$, is:

$$E(\Delta h'') = \left(h_2' - h_1\right) - \left(h_2' - h_2\right) = h_2 - h_1 = E(\Delta h) \tag{16}$$

Therefore:

$$E(\Delta h'') = \tilde{e}[pf_2(c_2^*) - c_2^*(1 + i_d)] + c_1^* + c_1^* i_d - pf_1(c_1^*) \tag{17}$$

For $E(\Delta h'') = E(\Delta h) > 0$, the increase in benefits for farmers who adopt early techniques is smaller. Moreover, the implication of this is that when farmers are early adopters of a technique, the expected income of them from adopting a new technique will decline, and thus, the willingness to adopt the new technique will also decline. In addition, Equation (17) can be understood as a "sunk cost", and it will reduce the willingness to convert technology [36]. Therefore, we obtain the third deduction.

Deduction 3. *Farmers' adoption of early technology will lower their adoption intentions to new technology.*

In this paper, with the help of the economic model, we were able to quantify the difference in expected returns of farmers adopting similar technologies. Compared with the existing literature [32,33], we used the marginal return to simplify the derivation process, and focused on the role of farmers' endowment. We also used figures to show the Deductions more clearly. Finally, aiming at the problems raised in the introduction, we were able to draw three inferences.

3. Data

3.1. Research Area

Our research sites are Yangling District and Jingyang County of Shaanxi Province, one of the main vegetables producing areas in Northwest China [37]. Yangling District is China's agricultural high-tech demonstration zone, with many agricultural high-tech enterprises and demonstration bases. As for Jingyang County, according to the government report, the vegetable output of it reached 1.82 million tons, with an output value of about 1.84 billion RMB in 2019 [38]. We selected two main vegetable producing towns in Jingyang County, Yunyang town and Anwu town, as well as Yangling District as the research locations, which are shown in Figure 3.

3.2. Sampling Survey

The survey time we chose is January 2020, when most farmers had returned to the village, to avoid the problem of insufficient interviewees. Then, before the formal investigation, we first learned about the village level division of each region, and randomly selected 19 villages, with an average of 6–7 villages in each region. After that, with the help of local governments, we obtained basic information of the villagers, such as gender and age, and determined the interviewees before the meeting. In total, 30–35 interviewees were randomly selected from each village. Finally, 353 questionnaires were collected, including 330 valid questionnaires. Of these, 94 are from Anwu Town, 132 from Yunyang town, and 104 from Yangling District.

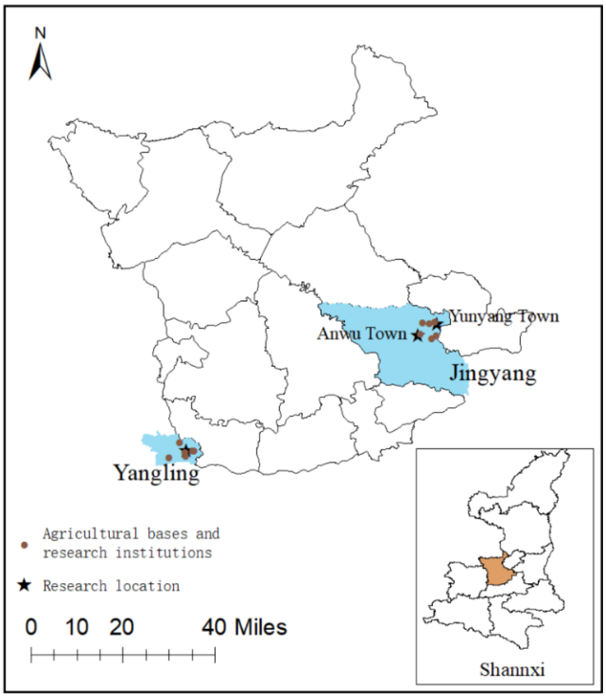

Figure 3. Areas and locations selected for the study.

Our purpose was to obtain information on farmers' technology adoption, technology understanding and production endowment. We chose land, labor force, and income as the three variables to represent farmers' endowment [39,40]. However, it is difficult to measure farmers' understanding of technology. Thus, referring to some of the literature, we used information processing capacity and information channels to reflect it [32,33]. For variables, we selected two basic variables, age and education, to reflect the information processing ability of farmers [32,41] and several channels from the perspective of individuals and social networks, respectively [42,43]. As for the dependent variables, referring to the practice of relevant studies [44,45], five subscales were used to measure farmers' adoption intentions to IICS. Since some farmers have adopted the early techniques, we used the data of adoption rather than the adoption intentions.

The descriptive statistics of the samples are shown in Table 1. The sample size obtained is more than 40 times the number of independent variables, which can better avoid the measurement error. From the sample data obtained, most of the features of the sample, such as education, land, and income, are evenly distributed. The distribution of age is mainly concentrated between 41–60 years old, which is more consistent with the average level of China.

3.3. Econometric Models

3.3.1. Logit Model

First, we consider the question of whether the factors affecting farmers' adoption of these two types of techniques are the same. According to the theory in Section 2, farmers' willingness and behavior depend on the expected benefits of adopting technology. In turn, the expected benefits depend on the farmers' endowment and understanding. Setting Y_e as the expected benefits and based on the classical linear hypothesis and existing research, we can get:

$$Y_e = \beta + \sum_{i=1}^{n} \alpha_i x_i + u \tag{18}$$

where x_i and α_i are the factors that may affect farmers' expected benefits and its corresponding coefficients. β and u are a constant term and a residual term. However, the expected return is an unobservable continuous variable. We can only observe the adoption behavior or intentions (Y), which is a classified variable. Moreover, there is a critical value K_0 (or multiple critical values K_1 and K_2), such that:

$$\begin{cases} Y = 1 & Y_e \geq K_0 \\ Y = 0 & Y_e < K_0 \end{cases} \quad or \begin{cases} Y = 3 & Y_e \geq K_2 \\ Y = 2 & K_2 < Y_e \geq K_1 \\ Y = 1 & Y_e < K_1 \end{cases} \tag{19}$$

The above model setting is a Binary Logit model (or Ordered Logit model) [33]. Therefore, we used Logit models to estimate the impact of these two factors on adoption or adoption intentions.

Table 1. Descriptive statistics of samples.

Classification	Variables	Types	Frequency (n)	Percentage (%)
Information processing capacity	Age	20–40 years old	40	12.12
		41–60 years old	229	69.39
		Over 60 years old	61	18.48
	Education	Under 6 years	87	26.36
		Primary school	92	27.87
		Junior high school	120	36.36
		High school education or Higher	31	9.39
Information Channels	Computer	Computer	166	50.30
	Training	Technical training	62	18.79
	Contract	Contract farming	93	28.18
	Relatives	Expert relatives or friends	70	21.21
Production characteristics	Land Area	<5 mu	93	28.18
		5–10 mu	197	59.70
		10–20 mu	35	10.61
		>20 mu	5	1.51
	Labor	<3 people	72	21.81
		3–5 people	194	58.78
		>5 people	64	19.39
	Gross household income	<10,000 yuan	11	3.33
		10,000–50,000 yuan	113	34.24
		50,000–100,000 yuan	100	30.30
		>100,000 yuan	106	32.12
Technology Adoption	Adoption Intention to IICS	Negative: 1–2	117	35.45
		Undefined: 3	95	28.79
		Positive: 4–5	118	35.76
	Adoption of early techniques	Venturi injector	52	15.76
		Differential pressure tank	20	6.06
		Others	8	2.42

Note: 1 mu = 0.07 acres. (n = 330).

3.3.2. Propensity Score Matching

Next, we examined the question of whether the adoption of early techniques will affect farmers' adoption of IICS, since farmers' adoption of early technology is not random, but self-selected behavior, leading to endogenous problems [46]. Factors such as income and labor affect early technology adoption, as well as adoption intentions to IICS. This will lead to endogenous problems and affect the unbiasedness of the estimation results. Because we use cross-sectional data, the method to deal with endogeneity is usually instrumental variable regression or PSM [47]. Since the two techniques are similar, it is difficult to find an effective instrumental variable. We choose PSM as the method to deal with endogeneity in this work.

PSM is a mature statistical method, which is widely used in survey data. The purpose of PSM is to select a subset from the dataset [48]. In this subset, except for the investigated variable (early technology adoption) and the outcome variable (adoption intentions to IICS), other factors influencing the core independent variable should be kept similar or the same as much as possible. The data in the subset are grouped according to different values of independent variables.

We first performed a regression with the investigated variable as the explained variable to determine the control variables. Due to sample limitations, this was only done for reference. Then, we categorized the farmers who were early adopters as the experimental group. The others were the unmatched control group. For each sample in the experimental group, we used the matching algorithms to select the sample similar to it in control variables from the unmatched control group and brought it into the matched control group. In this way, the subset was similar to the control variable method [49]. Then, the role of the core independent variable could be judged by the differences of the outcome variable in each group.

4. Results and Discussion

Empirical research needs to ensure the applicability of the model, as well as the accuracy and reliability of the results. Therefore, in addition to reporting the results and conclusions, we also conducted the applicability test, collinearity test, and robustness test to ensure that our empirical results are correct.

4.1. Logit Model for Deducation 1 and 2

4.1.1. Collinearity Test and Data Distribution Test

Since our model uses the labor force and income per unit of land, we also used the average data per mu for regression. Firstly, the Logit model requires that the Logit (p) $(Ln(p/(1-p))$ is linearly correlated with independent variables [50]. Therefore, we carried out the corresponding test through the scatter diagram (see Supplementary Materials for more details). The results show that the data distribution conforms to the assumption of the Logit model. Secondly, before Logit regression, a collinearity test was needed to avoid the distortion of model estimation caused by the high correlation between independent variables, which was carried out by the variance inflation factor (VIF) method. Specifically, VIF is the degree to which a given explanatory variable is explained by all other explanatory variables in the equation. Through the calculation of software SPSS, we obtained the results shown in Table 2. The VIF of each variable was less than 10, indicating that there was no obvious collinearity between independent variables. Furthermore, we considered the impact of Sample Selection Bias (SSB). Among the factors we investigated, there are two factors that may have SSB: contract and train. We conducted a Heckman test, and the significance of rho indicates whether the potential self-selected variables significantly affect the dependent variable, so we can judge whether there is SSB. As shown in Table 2, the test results (See supplementary materials for more details) show that there is no SSB (rho > 0.1).

Table 2. Results of the Collinearity Diagnostics and Heckman Test.

Variables	Tolerance	VIF
Labor	0.95	1.06
Income	0.95	1.05
Age	0.88	1.14
Education	0.86	1.17
Computer	0.93	1.08
Train	0.98	1.02
Contract	0.98	1.02
Relative	0.97	1.03
rho	**Early Techniques**	**IICS**
Train	0.433	0.830
Contract	0.586	0.219

4.1.2. Estimation Results of Logit Model

Next, we used SPSS to estimate the Logit model, and the results are shown in Table 3. For the adoption intentions of IICS, we use the ordered Logit model, which requires a proportional odds assumption (p-value > 0.05). The results show that the degree of freedom is 8, and the p-value is 0.26. This means that different degrees of adoption intentions follow the same law and the test passed.

Table 3. Estimation results.

Variables	Early Techniques			IICS		
	Estimate	p-Value	Std. E	Estimate	p-Value	Std. E
Labor	1.463	0.102	0.895	12.736 ***	0.000	0.929
Income	1.107 *	0.059	0.586	11.681 ***	0.000	1.098
Age	−1.341 *	0.078	0.761	−1.792 **	0.027	0.797
Education	2.199 **	0.025	0.980	2.356 **	0.041	0.951
Computer	0.628 **	0.032	0.292	0.576 **	0.048	0.289
Train	0.935 ***	0.004	0.328	0.739 **	0.041	0.354
Contract	0.897 ***	0.003	0.297	0.594 **	0.037	0.315
Relative	0.727 **	0.026	0.326	0.731 **	0.043	0.341

Note: *** Significant at the 1%. ** Significant at the 5%. * Significant at the 10%.

The regression results of the model are shown in Table 3. Firstly, for early techniques, the significance of farmers' endowment is small, in which the p-value of labor force is greater than 0.1 and that of capital is greater than 0.05. This means that farmers' endowments have no significant impact on the adoption of early techniques. However, they have a significant impact on the adoption intention to IICS (0.00 < 0.05; 0.00 < 0.05). This shows a great difference in the role of farmers' endowments under different technologies. Since the difference between the two types of technologies is mainly due to the adoption costs, it can be considered that Deduction 1 is verified.

We used information processing ability and information channels to reflect farmers' understanding of technology. For information processing ability, the role of age shows differences (p-value: 0.078 and 0.027), while the role of education is similar (p-value: 0.025 and 0.041). One possible reason is the early technology is relatively simple and easy to understand, the decline in understanding ability caused by age is not enough to affect. However, even with simple technology, basic education is still needed. Therefore, the role of education cannot be offset by the simplicity of the technology. Moreover, IICS technology is more complex and requires higher education and better understanding.

The significance of information channels is basically the same (all p-values lower than 0.05). This shows that whatever the technology, they have an important influence on the adoption. Specifically, the four variables reflect the four information channels: farmers themselves, extension agencies, agricultural enterprises, and social networks. Every channel is important and farmers will not only rely on a single one. In general, the significance of the factors that reflecting farmers' understanding is basically the same, and Deduction 2 is confirmed.

4.2. Propensity Score Matching for Deducation 3

In this work, we used the adoption intentions to IICS as the outcome variable of PSM, and used early technology adoption as the factor to be investigated. The software we used is Stata. Limited to data availability and sample size, we did not examine a wider range of covariates, but took the factors in Section 4.2 as covariates. Limited to the sample size, we used the nearest neighbor matching with sampling with replacement, and the matching ratio is 1:1. The frequency of farmers adopting early technology is 80, and the corresponding number of successful matches is 76. Due to the continuous covariates, these matches are fuzzy matches. The matching evaluation and balance test are shown in Tables 4 and 5. The results in Table 4 show that the difference between the matched control group and the experimental group is greatly reduced and not significant at the 10% level. Moreover, in Table 5, the deviation of each dimension between the matched experimental group and the control group is not significant at the level of 10%. These results mean that the matching result is acceptable.

Table 4. Overall evaluation of matching results.

Sample	Ps R2	LR chi2	p > chi2	Mean Bias	Med Bias
Unmatched	0.128	46.75	0.000	30.6	32.8
Matched	0.016	3.50	0.899	9.0	8.2

Table 5. Balance test results.

Variables	Matching Status	Mean		Std Dev	Change of Std Dev	Student's t Test	
		Treated	Control			t-Value	p-Value
Labor	Unmatched	0.259	0.245	8.76%	81.53%	0.656	0.513
	Matched	0.259	0.256	1.62%		0.102	0.919
Income	Unmatched	0.473	0.419	22.06%	41.58%	1.687	0.094
	Matched	0.473	0.503	−12.89%		−0.815	0.416
Age	Unmatched	0.596	0.666	−36.29%	84.42%	−2.771	0.006
	Matched	0.596	0.585	5.65%		0.358	0.721
Education	Unmatched	0.412	0.329	52.79%	90.43%	4.274	0
	Matched	0.412	0.405	5.05%		0.319	0.75
Computer	Unmatched	0.525	0.496	5.78%	100.00%	0.45	0.654
	Matched	0.525	0.525	0.00%		0	1
Training	Unmatched	0.2	0.184	4.05%	−123.03%	0.312	0.755
	Matched	0.2	0.238	−9.02%		−0.571	0.569
Contract	Unmatched	0.263	0.196	15.80%	6.52%	1.198	0.233
	Matched	0.263	0.2	14.77%		0.934	0.352
Realtives	Unmatched	0.262	0.288	−5.69%	49.97%	−0.446	0.657
	Matched	0.262	0.25	2.85%		0.18	0.857

By comparing the mean of dependent variables in the control group and the experimental group, the Average Treatment Effect (ATT) is used to investigate the role of characteristic factors [51]. The average treatment effect for the treated group (ATT) of early technology adoption is shown in Table 6. The t-value of the average processing effect before matching is 3.07 (>1.96), indicating that ATT is significant. The average adoption intentions to IICS under the adoption of early technology is 1.728, while the average adoption of farmers who are not early adopters of technology is 2.025. However, after matching, ATT is −0.125 and no longer significant (|−0.09| < 1.96). The results of PSM show that early technology adoption does not affect farmers' willingness to adopt IICS, which contradicts Deduction 3.

Table 6. ATE of early technology adoption on new technology adoption intention.

Sample	Treated	Control	ATT	t-Value
Unmatched	2.025	1.728	0.297	3.07
Matched	2.025	2.0375	−0.0125	−0.09

4.3. Discussion

The Logit model and PSM were used to verify our three deductions. The result is to accept Deductions 1 and 2, but reject Deduction 3.

First, labor and income are the factors to measure endowment, in which labor force can earn remuneration and can be put it into production, or directly into production, and farmers' income can also be directly put into production. Deduction 1 shows that endowment only affects high-cost technology adoption. This means that the cost of early fertigation techniques is low and most farmers can afford it. However, for the high-cost IICS, farmers' endowment plays an important role. The above conclusions are different from previous studies, which showed that higher endowment usually leads to higher adoption intention [11,17]. For example, the study of Jayne [52], which focused on Africa, found that the adoption level of high-income farmers is high. The results of Brown [53] showed that the same is true of human capital. However, our results show that this is not entirely correct. The possible reason for this difference is that the technology adoption cost considered in the above research is generally higher than the endowment of farmers.

According to our interest rate analysis, the above difference is because of the higher cost of borrowing funds. This comparison shows that the increase of endowments does not always improve the adoption or adoption intentions, but plays a role in a certain range. Therefore, subsidy policies are not always effective; some studies have found that subsidies can even lead to the abuse of production technology [54].

Secondly, the verification of Deduction 2 emphasizes the importance of farmers' understanding of technology, which affects the adoption of both types of technologies. Specifically, we divide the factors about farmer's understanding into two categories: farmers' information processing ability and information channels. The complexity of technology will also affect the role of farmers' information processing ability to a certain extent, leading to an inconsistency of the role of age. Similarly, Moges and Taye [15] explained this correlation as a positive correlation between farmers' education and cognition, and a high cognitive level can improve the adoption level. Most studies have found that young and highly educated farmers have a higher adoption level, which is similar to our conclusion [1,17,24]. However, some studies have found that demographic variables do not continue to play a role, but depend on the complexity of technology [55].

As for the four information channels, their effects are significant and consistent between the two types of technologies. This is completely consistent with most studies [15,26,27]. Information channels can improve the timeliness and accuracy of farmers' access to information, so as to help establish a higher level of understanding [27]. Specifically, training can improve the willingness to adopt as well as social learning [18,56].

Farmers' understanding not only affects decision-making before technology adoption but also the output after technology adoption. Esther et al. found that due to the lack of understanding of technology, farmers' income is often not as expected, and will also affect others' adoption through social networks [57].

Finally, the rejected Deduction 3 shows that early technology adoption will not affect the adoption intentions to IICS. As mentioned above, the cost of early technology is regarded as a "sunk cost", and this is the basis of our deduction. However, it may have other benefits in addition to economic losses. For example, the experience brought and the reuse of some equipment will improve farmers' adoption intentions. As pointed out by Garcia and Calantone, due to similar technologies, the difficulty of adoption will also be reduced, so as to improve the willingness to adopt [21,22], which may offset the impact of depressed costs.

4.4. Robustness Test

To ensure the reliability of the results, we conducted a robustness test. We used the Heterogeneous Selection Model (HCM) to test the results of Logit model [58]. Tables 7 and 8 show the heterogeneity of each variable and the corresponding estimation results. For the Logit model, only the heterogeneity of age is positive (0.042 < 0.05), but the parameter estimation results are consistent with those in Section 4.1. Moreover, for the ordered Logit regression, the heterogeneity of education (0.007 < 0.1), train (0.082 < 0.1), and computer (0.090 < 0.1) are positive. These indicate that heterogeneity exists. However, the parameter estimation results are also consistent with those in Section 4.1. In general, the variation of estimation results considering heterogeneity is small, and the variation of likelihood is also small, showing that heterogeneity does not affect the reliability of the results.

Table 7. Heterogeneity test and results for early techniques.

Variables	Heterogeneity Variables Investigated for Early Techniques							
	Labor	Income	Age	Education	Computer	Train	Contract	Relative
Labor	1.49	0.999	0.293	1.8	1.763 **	1.109 *	1.535 **	1.165 **
Income	1.98 **	1.591 **	0.357	2.045	1.822 *	1.465	1.382	1.269
Age	−1.34	−1.193	0.183	−2.328	−2.42 *	−1.346 *	−1.165	−1.264 *
Education	2.01 **	2.072 **	0.662 *	1.311	2.577 *	2.2 **	3.622 **	1.689 *
Computer	1.76 *	0.58 *	0.189 *	0.918 *	0.044	0.629 **	0.725 **	0.453
Train	2 **	0.855 **	0.312 **	1.325 **	1.187 ***	0.93 **	1.022 ***	0.867 ***
Contract	2.26 **	0.833 **	0.236 *	1.537 *	1.219 ***	0.898 ***	0.252	0.816 ***
Relative	1.84 *	0.673 *	0.205 *	1.117 *	1.012 **	0.727 **	0.719 *	0.933 ***
Lnsigma	0.868	−0.326	−2.243	1.105	0.579	0.008	0.785	−0.511
p-value	0.224	0.798	0.042	0.309	0.145	0.985	0.189	0.191
Log likelihood	−159.09	−159.83	−157.44	−159.23	−158.76	−159.85	−158.63	−159.08

Note: *** Significant at the 1%. ** Significant at the 5%. * Significant at the 10%.

Table 8. Heterogeneity test and results for IICS.

Variables	Heterogeneity Variables Investigated for IICS							
	Labor	Income	Age	Education	Computer	Train	Contract	Relative
Labor	12.913 ***	11.69 ***	11.669 ***	7.58 ***	13.994 ***	11.062 ***	12.981 ***	11.07 ***
Income	13.916 ***	12.68 ***	12.657 ***	8.145 ***	14.823 ***	12.06 ***	13.958 ***	11.922 ***
Age	−1.982 **	−1.765 **	−1.761 *	−1.05 **	−2.157 **	−1.73 **	−1.855 **	−1.643 **
Education	2.478 **	2.332 **	2.327 **	1.896 ***	2.886 **	2.046 **	2.808 **	2.243 **
Computer	0.654 *	0.571 *	0.57 *	0.329 *	0.564 *	0.479 *	0.616 *	0.591 **
Train	0.798 **	0.722 **	0.721 *	0.406 *	0.954 **	0.762 ***	0.792 **	0.66 **
Contract	0.743 **	0.656 **	0.655 *	0.355 *	0.764 **	0.624 **	0.631 *	0.625 **
Relative	0.743 *	0.689 *	0.687 *	0.461 **	0.727 *	0.634 **	0.748 **	0.727 **
Lnsigma	0.367	0.681	0.435	0.474	0.172	0.235	0.180	0.211
p-value	0.534	0.997	0.993	0.007	0.090	0.127	0.082	0.148
Log likelihood	−175.00	−175.20	−175.20	−171.38	−173.77	−174.04	−173.64	−174.16

Note: *** Significant at the 1%. ** Significant at the 5%. * Significant at the 10%.

Then, we consider the impact of region. As Anwu town and Yunyang town are both located in Jingyang County, while Yangling District is far away from them, we added geographical location as a dummy variable to test the role of space. The results are shown in Table 9. We can see that its effect is not significant (0.487 > 0.05; 0.346 > 0.05). Although in the Logit model, the significance of labor and income have been improved, they are still not significant at the 5% level. The estimation results of other parameters are basically the same as those in Section 4.1. The results show that our results are not affected by geographical location.

Table 9. Impact of geographical location.

Variables	Early Techniques			IICS		
	Estimate	*p*-Value	Std. E	Estimate	*p*-Value	Std. E
Labor	1.494 *	0.096	0.897	12.876 ***	0.000	1.483
Income	1.122 *	0.059	0.587	11.769 ***	0.000	1.056
Age	−1.335 *	0.080	0.762	−1.817 **	0.023	0.798
Education	2.129 **	0.030	0.983	2.251 **	0.018	0.952
Computer	0.637 **	0.029	0.293	0.590 **	0.042	0.290
Train	0.930 ***	0.005	0.328	0.719 **	0.041	0.352
Contract	0.904 ***	0.002	0.298	0.676 **	0.033	0.316
Relative	0.745 **	0.023	0.327	0.706 **	0.038	0.340
Location [1]	−0.215	0.487	0.310	0.283 **	0.346	0.301

Note: [1] Jingyang County or Yangling District. *** Significant at the 1%. ** Significant at the 5%. * Significant at the 10%.

Finally, we consider the influence of outliers. The results of the boxplot (Supplementary Materials) show that there are possible outliers in data. Therefore, we conduct regression again after eliminating the outliers, and the results are shown in Table 10. We can see that the difference between these and the results in Section 4 is small, indicating that the outliers have less impact on the robustness of the results. Moreover, the above shows that our results are robust on the whole.

Table 10. Estimation results after excluding outliers.

Variables	Early Techniques			IICS		
	Estimate	*p*-Value	Std. E	Estimate	*p*-Value	Std. E
Labor	1.562 *	0.085	0.907	12.652 ***	0.000	1.462
Income	1.221 *	0.056	0.639	11.645 ***	0.000	1.072
Age	−1.092	0.204	0.861	−1.764 **	0.042	0.869
Education	2.427 **	0.017	1.017	2.230 **	0.020	0.959
Computer	0.699 **	0.022	0.304	−0.678 **	0.021	0.294
Train	0.854 **	0.012	0.339	−0.691 *	0.057	0.362
Contract	1.007 ***	0.001	0.309	−0.607 *	0.058	0.320
Relative	0.719 **	0.036	0.343	−0.694 **	0.044	0.345

Note: *** Significant at the 1%. ** Significant at the 5%. * Significant at the 10%.

5. Conclusions

Based on the existing research [32,33], we set up an expected benefits model of farmers' adoption, and analyzed the impact of farmers' endowment, understanding of technology, and early technology adoption on their intentions to adopt IICS. Based on the survey data of the research group, we used the Logit model and PSM to analyze the factors that may affect farmers' adoption intentions to IICS. Among them, the Logit model was used to investigate two kinds of factors: farmers' endowment and farmers' understanding. PSM aimed to reduce the impact of endogeneity, and thus, to more accurately estimate the impact of early technology adoption on IICS.

The main conclusions are: (1) The role of farmers' endowment (labor and income) depends on the cost of technology adoption. When considering the low-cost early fertigation techniques, it does not play a role, while farmers' endowments have a significant impact on the willingness to adopt IICS; (2) Farmers' understanding of techniques always has a significant impact; (3) Early technology adoption will not affect adoption intentions to adopt IICS.

Based on the above, in order to better promote IICS, we not only need to strengthen technical training for farmers, but also give them appropriate subsidies. The above measures can not only strengthen farmers' understanding of technologies, but also balance the technology gap between them, so as to narrow the poverty gap in rural areas. Secondly, the adoption of higher level IICS can alleviate the shortage of rural labor force as a whole, improve farmers' income and narrow the urban–rural gap. Moreover, due to the efficient and intelligent use of fertilizer by IICS, the environmental pollution problems in rural and agricultural areas can be curbed. Finally, farmers who adopt early technology may have gained experience in fertigation, and some facilities can also be applied in IICS to reduce investment. Therefore, we believe that it is unnecessary to give these farmers special subsidies. This will effectively avoid the mismatch of agricultural extension policies and improve the effectiveness of policies.

PSM can only eliminate the influence of some unobserved heterogeneity, so a wider range of covariate investigation is required to improve the reliability of the results. The data we obtained are limited to Shaanxi Province, which may lead to insufficient reliability of the results. Therefore, a wider range of investigation and research is needed in the future. Moreover, due to the insufficient adoption of IICS, we used the adoption intentions of IICS as a substitute. However, intention is not the same as behavior, and this decision might have reduced the reliability of the conclusion. In the research literature on technology adoption, few studies have focused on the impact of early technology adoption on technology renewal. For some countries and regions with rapid development, this is a prominent problem and worthy of in-depth analysis.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/agriculture11100913/s1, Questionnaires; Outliers Test; Model adaptability Test; Original Report for Heckman Test.

Author Contributions: Conceptualization, J.Y. and X.L.; methodology, J.Y. and X.L.; software, X.L.; validation, J.R. and Z.S.; formal analysis, J.Y. and X.L.; investigation, J.Y., X.L., J.R. and Z.S.; data curation, J.R. and Z.S.; writing—original draft preparation, J.Y.; writing—review and editing, J.R. and Z.S.; funding acquisition, J.R. and Z.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Nature Science Foundation of China (71973106), National Key Research and Development Project, (2019YFD1101103), Key Scientific Research Projects of Shaanxi Provincial Department of Education (21JT043) and Tang Scholar of Northwest A&F University.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ma, L.; Ni, J.; Fleskens, L.; Wang, H.; Xuan, Y. Modelling Fertilizer Use in Relation to Farmers' Household Characteristics in Three. *Agriculture* **2021**, *11*, 472. [CrossRef]
2. Azad, N.; Behmanesh, J.; Rezaverdinejad, V.; Abbasi, F.; Navabian, M. Developing an optimization model in drip fertigation management to consider environmental issues and supply plant requirements. *Agric. Water Manag.* **2018**, *208*, 344–356. [CrossRef]
3. Fan, J.; Lu, X.; Gu, S.; Guo, X. Improving nutrient and water use efficiencies using water-drip irrigation and fertilization tech-nology in Northeast China. *Agric. Water Manag.* **2020**, *241*, 106352. [CrossRef]
4. Cui, Y.; Meng, J.; Lu, C. Recent developments in China's labor market: Labor shortage, rising wages and their implications. *Rev. Devel. Econ.* **2018**, *22*, 1217–1238. [CrossRef]
5. Lu, H.; Xie, H. Impact of changes in labor resources and transfers of land use rights on agricultural non-point source pollution in Jiangsu Province, China. *J. Environ. Manag.* **2018**, *207*, 134–140. [CrossRef]
6. Xu, D.-D.; Cao, S.; Wang, X.-X.; Liu, S.-Q. Influences of labor migration on rural household land transfer: A case study of Sichuan Province, China. *J. Mt. Sci.* **2018**, *15*, 2055–2067. [CrossRef]
7. Xu, Y.; Huang, X.; Bao, H.X.H.; Ju, X.; Zhong, T.; Chen, Z.; Zhou, Y. Rural land rights reform and agri-environmental sustainability: Empirical evidence from China. *Land Use Policy* **2018**, *74*, 73–87. [CrossRef]
8. Bamurigire, P.; Vodacek, A.; Valko, A.; Ngoga, S.R. Simulation of Internet of Things Water Management for Efficient Rice Irrigation in Rwanda. *Agriculture* **2020**, *10*, 431. [CrossRef]
9. Li, H.; Tang, P.; Chen, C.; Zhang, Z.; Xia, H. Research status and development trend of fertilization equipment used in fertigation in China. *J. Drain. Irrig. Machin. Eng.* **2021**, *39*, 200–209. (In Chinese)
10. Ruan, J.; Jiang, H.; Li, X.; Shi, Y.; Chan, F.T.S.; Rao, W. A Granular GA-SVM Predictor for Big Data in Agricultural Cyber-Physical Systems. *IEEE Trans. Ind. Inform.* **2019**, *15*, 6510–6521. [CrossRef]
11. Yang, Q.; Zhu, Y.; Wang, J. Adoption of drip fertigation system and technical efficiency of cherry tomato farmers in Southern China. *J. Clean. Prod.* **2020**, *275*, 123980. [CrossRef]
12. Magruder, J.R. An Assessment of Experimental Evidence on Agricultural Technology Adoption in Developing Countries. *Annu. Rev. Resour. Economics* **2018**, *10*, 299–316. [CrossRef]
13. Yang, Q.; Zhu, Y.; Wang, F. Exploring Mediating Factors between Agricultural Training and Farmers' Adoption of Drip Fer-tigation System: Evidence from Banana Farmers in China. *Water* **2021**, *13*, 1364. [CrossRef]
14. Suvedi, M.; Ghimire, R.; Kaplowitz, M. Farmers' participation in extension programs and technology adoption in rural Nepal: A logistic regression analysis. *J. Agric. Educ. Ext.* **2017**, *23*, 351–371. [CrossRef]
15. Moges, D.M.; Taye, A.A. Determinants of farmers' perception to invest in soil and water conservation technologies in the North-Western Highlands of Ethiopia. *Int. Soil Water Conserv. Res.* **2017**, *5*, 56–61. [CrossRef]
16. Bramley, R.G.V.; Ouzman, J. Farmer attitudes to the use of sensors and automation in fertilizer decision-making: Nitrogen fertilization in the Australian grains sector. *Precis. Agric.* **2019**, *20*, 157–175. [CrossRef]

17. Kaliyeva, S.; Areal, F.; Gadanakis, Y. Would Kazakh Citizens Support a Milk Co-Operative System? *Agriculture* **2021**, *11*, 642. [CrossRef]
18. Miller, N.J.; Griffin, T.W.; Bergtold, J.; Ciampitti, I.A.; Sharda, A. Farmers' Adoption Path of Precision Agriculture Technology. *Adv. Anim. Biosci.* **2017**, *8*, 708–712. [CrossRef]
19. Abro, Z.A.; Jaleta, M.; Teklewold, H. Does Intensive Tillage Enhance Productivity and Reduce Risk Exposure? Panel Data Evidence from Smallholders' Agriculture in Ethiopia. *J. Agric. Econ.* **2018**, *69*, 756–776. [CrossRef]
20. Mao, H.; Luo, X.; Tang, L.; Huang, Y. Adoption decisions of multiple agricultural green production technologies: Explanatory factors and correlation analysis. *J. China Agric. Univ.* **2021**, *26*, 231–244. (In Chinese)
21. Garcia, R.; Calantone, R. A critical look at technological innovation typology and innovativeness terminology: A literature review. *J. Prod. Innov. Manag.* **2002**, *19*, 110–132. [CrossRef]
22. Hasler, K.; Olfs, H.-W.; Omta, O.; Bröring, S. Drivers for the Adoption of Different Eco-Innovation Types in the Fertilizer Sector: A Review. *Sustainability* **2017**, *9*, 2216. [CrossRef]
23. Nadia, A.; Shahrina, M.; Mohamad, A.B.; Ahmad, H. A state-of-the-art review on facilitating sustainable agriculture through green fertilizer technology adoption: Assessing farmers behavior. *Trends Food Sci. Technol.* **2019**, *86*, 439–452.
24. Zerssa, G.; Feyssa, D.; Kim, D.-G.; Eichler-Löbermann, B. Challenges of Smallholder Farming in Ethiopia and Opportunities by Adopting Climate-Smart Agriculture. *Agriculture* **2021**, *11*, 192. [CrossRef]
25. Bukchin, S.; Kerret, D. The role of self-control, hope and information in technology adoption by smallholder farmers—A moderation model. *J. Rural. Stud.* **2020**, *74*, 160–168. [CrossRef]
26. Emerick, K.; Dar, M.H. Farmer Field Days and Demonstrator Selection for Increasing Technology Adoption. *Rev. Econ. Stat.* **2021**, *103*, 1–14. [CrossRef]
27. Nakano, Y.; Tsusaka, T.; Aida, T.; Pede, V.O. Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania. *World Dev.* **2018**, *105*, 336–351. [CrossRef]
28. Baumgart-Getz, A.; Prokopy, L.S.; Floress, K. Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. *J. Environ. Manag.* **2012**, *96*, 17–25. [CrossRef]
29. Wassie, A.; Pauline, N. Evaluating smallholder farmers' preferences for climate smart agricultural practices in Tehuledere District, northeastern Ethiopia. *Singap. J. Trop. Geogr.* **2018**, *39*, 300–316. [CrossRef]
30. Mishra, B.; Gyawali, B.R.; Paudel, K.P.; Poudyal, N.C.; Simon, M.F.; Dasgupta, S.; Antonious, G. Adoption of Sustainable Agriculture Practices among Farmers in Kentucky, USA. *Environ. Manag.* **2018**, *62*, 1060–1072. [CrossRef]
31. Takahashi, K.; Muraoaka, R.; Otsuka, K. Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agric. Econ.* **2019**, *51*, 31–45. [CrossRef]
32. Atanu, S.; Love, H.A.; Schwart, R.; Saha, A. Adoption of Emerging Technologies Under Output Uncertainty. *Am. J. Agric. Econ.* **1994**, *76*, 836–846. [CrossRef]
33. Kong, X.; Fang, S.; Pang, X.; Ma, J. Analysis of the effect of household endowments on the agricultural technology adoption decision in west China. *Econ. Res. J.* **2004**, *12*, 122–195. (In Chinese)
34. Mas-Colell, A.; Michael, W.; Jerry, G. *Microeconomic Theory*; Oxford University Press: Oxford, UK, 1995.
35. Wossen, T.; Abdoulaye, T.; Alene, A.; Haile, M.G.; Feleke, S.; Olanrewaju, A.; Manyong, V. Impacts of extension access and cooperative membership on technology adoption and household welfare. *J. Rural. Stud.* **2017**, *54*, 223–233. [CrossRef]
36. Dumortier, J.; Kauffman, N.; Hayes, D.J. Production and spatial distribution of switchgrass and miscanthus in the United States under uncertainty and sunk cost. *Energy Econ.* **2017**, *67*, 300–314. [CrossRef]
37. Sawut, R.; Kasim, N.; Maihemuti, B.; Hu, L.; Abliz, A.; Abdujappar, A.; Kurban, M. Pollution characteristics and health risk assessment of heavy metals in the vegetable bases of northwest China. *Sci. Total. Environ.* **2018**, *642*, 864–878. [CrossRef] [PubMed]
38. 2019 Jingyang Vegetable Industry Development Report. Available online: http://www.snjingyang.gov.cn/gk/wuxianggongkai/jieguogongkai/79128.htm (accessed on 27 June 2021).
39. Lu, H.; Hu, L.; Zheng, W.; Yao, S.; Qian, L. Impact of household land endowment and environmental cognition on the willing-ness to implement straw incorporation in China. *J. Clean. Prod.* **2020**, *262*, 121479. [CrossRef]
40. Dill, M.D.; Emvalomatis, G.; Saatkamp, H.; Rossi, J.A.; Pereira, G.; Barcellos, J. Factors affecting adoption of economic management practices in beef cattle production in Rio Grande do Sul state, Brazil. *J. Rural. Stud.* **2015**, *42*, 21–28. [CrossRef]
41. Lundström, C.; Lindblom, J. Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to Foster farming practices: The case of CropSAT. *Agric. Syst.* **2018**, *159*, 9–20. [CrossRef]
42. McCord, P.F.; Cox, M.; Schmitt-Harsh, M.; Evans, T. Crop diversification as a smallholder livelihood strategy within semi-arid agricultural systems near Mount Kenya. *Land Use Policy* **2015**, *42*, 738–750. [CrossRef]
43. Madhava, C.; Pillai, U.S. Effect on Crop Yield and Perceptions of Farmers on Drip Fertigation: Study From Kerala State, India. *Inter. J. Sci. Res.* **2015**, *4*, 10.
44. Zeweld, W.; Van Huylenbroeck, G.; Tesfay, G.; Speelman, S. Smallholder farmers' behavioural intentions towards sustainable agricultural practices. *J. Environ. Manag.* **2017**, *187*, 71–81. [CrossRef] [PubMed]
45. Van Winsen, F.; de Mey, Y.; Lauwers, L.; van Passel, S.; Vancauteren, M.; Wauters, E. Cognitive mapping: A method to elucidate and present farmers' risk perception. *Agric. Syst.* **2013**, *122*, 42–52. [CrossRef]

46. Ma, W.; Renwick, A.; Yuan, P.; Ratna, N. Agricultural cooperative membership and technical efficiency of apple farmers in China: An analysis accounting for selectivity bias. *Food Policy* **2018**, *81*, 122–132. [CrossRef]
47. Benedetto, U.; Head, S.J.; Angelini, G.D.; Blackstone, E.H. Statistical primer: Propensity score matching and its alternatives. *Eur. J. Cardio-Thoracic Surg.* **2018**, *53*, 1112–1117. [CrossRef]
48. Rosenbaum, P.R.; Rubin, D.B. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* **1983**, *70*, 41–55. [CrossRef]
49. Yongnam, K.; Peter, S. Quasi-Experimental Designs for Causal Inference. *Educ. Psychol.* **2016**, *51*, 395–405.
50. Norton, E.C.; Dowd, B.E. Log Odds and the Interpretation of Logit Models. *Health Serv. Res.* **2018**, *53*, 859–878. [CrossRef]
51. Caliendo, M.; Kopeinig, S. Some Practical Guidance for The Implementation of Propensity Score Matching. *J. Econ. Surv.* **2008**, *22*, 31–72. [CrossRef]
52. Jayne, T.; Snapp, S.; Place, F.; Sitko, N. Sustainable agricultural intensification in an era of rural transformation in Africa. *Glob. Food Secur.* **2019**, *20*, 105–113. [CrossRef]
53. Brown, B.; Nuberg, I.; Llewellyn, R. Negative evaluation of conservation agriculture: Perspectives from African smallholder farmers. *Int. J. Agric. Sustain.* **2017**, *15*, 467–481. [CrossRef]
54. Wu, H.; Ge, Y. Excessive Application of Fertilizer, Agricultural Non-Point Source Pollution, and Farmers' Policy Choice. *Sustainability* **2019**, *11*, 1165. [CrossRef]
55. Ahmad, N. Descriptive Study of Cucumber Farmers' Awareness and Perception in 'Jordan Valley' Toward Fertigation Technology. *Am. Eurasian J. Agric. Environ. Sci.* **2011**, *11*, 857–862.
56. Genius, M.; Koundouri, P.; Nauges, C.; Tzouvelekas, V. Information Transmission in Irrigation Technology Adoption and Dif-fusion: Social Learning, Extension Services, and Spatial Effects. *Am. J. Agric. Econ.* **2014**, *96*, 328–344. [CrossRef]
57. Duflo, E.; Kremer, M.; Robinson, J. Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *Am. Econ. Rev.* **2009**, *101*, 2350–2390. [CrossRef]
58. Williams, R. Using Heterogeneous Choice Models to Compare Logit and Probit Coefficients Across Groups. *Sociol. Methods Res.* **2009**, *37*, 531–559. [CrossRef]