Public Agricultural Extension, Pest and Disease Experience, and Adoption of Improved Wheat Varieties

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Abstract

Improved varieties are considered critical for increasing crop yields worldwide. This study explored the effects of public agricultural extension and pest and disease experience on adoption of improved varieties using survey data on 525 wheat farmers in Anhui Province, China, to which the Heckman sample selection model was applied. The results showed that public agricultural extension had a significant positive relationship with adoption of improved varieties. Demonstration and training, as different forms of agricultural extension, both increased the probability of farmers adopting improved varieties, but only demonstration had a marked effect on degree of adoption. Pest and disease experience increased the probability of adoption of improved varieties by farmers and significantly enhanced the effect of public agricultural extension, but did not affect degree of adoption. Further analysis using an endogenous switching regression model revealed that adoption of improved varieties raised wheat yields by around 337.83 kg/ha. Public agricultural extension should thus be strengthened, especially for farmers with pest and disease experience, and a diversified, well-functioning agricultural extension system should be provided.

Keywords

improved varieties; wheat production; farmers' adoption; endogenous switching regression (ESR) model; Heckman sample selection model

1 Introduction

Agriculture is one of the sectors most clearly affected by climate change, and global food security will be greatly challenged and shocked in the next 30 years (GOUVEA et al., 2022; WOUTERSE et al., 2022). Use of improved varieties will be important to increase future crop yields and adapt to climate change (SHI et al., 2021; VEETTIL et al., 2021; BAIRAGI et al., 2021). According to BRUINS (2009), improved crop varieties account for approximately 50-90% of the increase achieved to date in global crop yields. Replacement of outdated varieties will also enhance food security, as the likelihood of food security increases by on average 2.9% for each unit increase in area of improved crop varieties (SHIFERAW et al., 2014). However, farmers in developing countries are often slow to act when they encounter improved varieties (KRISHNAN and PATNAM, 2014). For example, a recent survey in China's important wheat-producing regions found that around 47% of farmers have still not adopted wheat varieties with drought resistance (ZHENG et al., 2021).

Agricultural extension is considered a key tool for bridging the gap between new technologies and farmers (KUMAR et al., 2020; WUEPPER et al., 2021; CAI et al., 2022). In developing countries, especially China, agricultural extension services are mainly provided by a public extension system. It is estimated that China has around 500,000 extension agents providing services to farmers (DENG et al., 2021). Agricultural extension helps farmers become better managers by accelerating knowledge transfer and changing farmers' cautious attitudes to new technology adoption (NORTON and ALWANG, 2020; OGUTU et al., 2020; EMERICK and DAR, 2021; YITAYEW et al., 2021), which has the potential to increase agricultural productivity and sustainability potential (DJURAEVA et al., 2023). For example, in their choice of pest management strategies, farmers who receive public extension advice have been found to be more likely to use preventive measures rather than pesticides (WUEPPER et al., 2021). DENG et al. (2021) found that public agricultural extension made a significant contribution to agricultural productivity growth in China, with a real return of 29%.

Although the literature mainly reports high utility of public agricultural extension, some studies have found different outcomes (BENYISHAY and MOBARAK, 2019; KONDYLIS et al., 2017; PAN et al., 2017). Top-down "transfer of technology" model is ineffective in

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many environments, while teaching models developed in the absence of farmer understanding are not successful in building farmer capacity (NORTON and ALWANG, 2020). FAN et al. (2022) found no direct effect of agricultural extension systems on farmers' adoption of conservation agriculture, while a study in Uganda showed that adoption rates of improved seeds did not change significantly as a result of promotion of training courses (PAN et al., 2018). The form of participation in extension seems to be important in explaining differences in farmers' technical efficiency (DJURAEVA et al., 2023). Against this background, in the present study we attempted to clarify the impact of public agricultural extension on farmers' adoption behavior regarding improved varieties and the differences in outcome between different forms of extension.

Natural disasters caused by climate change inevitably have an important impact on agricultural production. Planting improved varieties is one of the management strategies widely used by farmers to mitigate this impact. BOZZOLA and SMALE (2020) concluded that farmers who have experienced floods or crop diseases are more likely to adopt modern varieties, while in a study on adoption of drought-tolerant maize varieties in Malawi, KATENGEZA et al. (2019) found that intensity of adoption by farmers was influenced by previous drought experience. In contrast, CAVATASSI et al. (2011) found that farmers in eastern Ethiopia who were most vulnerable to extreme weather events were less likely to use modern varieties. Similarly, in a variety adoption study on Chinese maize farmers, BAI et al. (2015) found that occurrence of severe weather in the previous season led to a tendency for farmers to plant fewer new varieties and to allocate more land to older varieties. Lack of information on improved varieties may be the main reason why farmers rely heavily on older varieties (NAZLI and SMALE, 2016; YITAYEW et al., 2021). This seems to suggest that there is an interactive effect between public agricultural extension and pest and disease experience on adoption of improved varieties by farmers.

Wheat is an important food crop in China, accounting for 40% of grain consumption (LIU et al., 2022). However, the longer growth cycle in wheat compared with other food crops results in wheat being more vulnerable to natural disasters. In this study, we focused on disasters caused by pests and diseases, which have been identified as an important cause of wheat yield loss in China (ZHANG et al., 2022), and examined how public agricultural extension and farmers' pest and disease experiences affect farmers' adoption of improved varieties. In an empirical study using survey data from 525 wheat farmers in Anhui Province, China, we included public agricultural extension and farmers' pest and disease experience in the analytical framework, analyzed the effects of public agricultural extension in different forms, and assessed the intrinsic link between pest and disease experience and public agricultural extension. Diffusion of improved varieties is an ongoing dynamic process, and farmers' adoption decisions are not necessarily binary and differ in the intensity of adoption. Therefore, we applied the Heckman sample selection model to the data.

The aim of the study was to shed light on three issues. First, instead of focusing on the effects of a single agricultural extension pathway (RAGASA, 2020; TAYLOR and BHASME, 2018; MORGAN et al., 2020), we considered both training and demonstration efforts. This was done in order to obtain a more comprehensive understanding of the effects of different forms of agricultural extension on adoption of improved varieties by farmers, and also to act as reference when evaluating diffusion of improved varieties. Second, we included pest and disease experience, public agricultural extension, and adoption of improved varieties by farmers in a single analytical framework, to assess whether pest and disease experience is effective in stimulating the effects of public agricultural extension. This issue has rarely been addressed in previous studies, which have mostly considered disaster experience as a variable influencing farmers' adoption of technology (TAN-SOO et al., 2023). Third, we assessed the impact of adoption of improved varieties on farm performance (wheat production) by using an endogenous switching regression (ESR) model to determine whether improved varieties could achieve the desired effect of improving farm performance.

The remainder of the paper is organized as follows: Section 2 introduces the theoretical framework and research hypotheses. Section 3 explains the data sources, variable selection, and model construction. Section 4 presents and discusses the empirical evidence obtained. Section 5 lists policy implications of the empirical results and Section 6 presents conclusions from the work.

2 Theoretical Framework

2.1 Public Agricultural Extension and Farmers' Adoption Behavior regarding Improved Varieties

Diffusion of innovation theory defines diffusion as the process by which an innovation spreads through a period of time, through specific channels, among members of a particular social system (ROGERS, 1983). According to the theory, farmers' decision-making process on adoption of improved varieties is an information-seeking and information-processing behavior through which individuals strive to reduce the uncertainty of new technologies. In China, public agricultural extension is the main channel for disseminating scientific and technological innovations and promoting their transformation. This transfer of knowledge and information means that farmers are better able to make technology adoption decisions and improve farm management (FAN et al., 2022). Adoption of improved varieties by farmers is the outcome of a careful trade-off between "profit-driven" and "risk-averse" (RUHINDUKA et al., 2020; BUEHREN et al., 2019). The effectiveness of public agricultural extension depends on the form of extension (training, demonstration, field days, etc.) (MAERTENS et al., 2021). This study focused on two of these forms, training and demonstration.

Training is an effective way to promote adoption of new technology by imparting knowledge to farmers through presentations and on-site displays. This can improve farmers' cognitive level and thus promote diffusion and spread of new technologies (LIU et al., 2019). PAN et al. (2017) found a significant positive relationship between training and new technology adoption by farmers, with hands-on and on-site forms of training appearing to have the best effect. However, the amount of work and costs involved in directly training and guiding all farmers can be prohibitively high, and only relatively few farmers can benefit (TAKAHASHI et al., 2020). Moreover, in some cases the role of farmer training in the uptake of extension advice may be overstated (DZANKU and OSEI, 2022). Although training increases the adoption of recommended practices and improves performance, not all trainees adopt all practices (FAFCHAMPS et al., 2020).

Demonstration, another key form of public agricultural extension, achieves technology diffusion and extension cost savings by selecting a small number of farmers in a village to be mentored by agricultural technicians. These selected farmers then train and share knowledge with their peers (MORGAN et al., 2020). This approach is deeply rooted in the concept of social learning, which maximizes and accelerates diffusion of information and technology in a rural society of acquaintances (RAGASA, 2020; LIU et al., 2019). Demonstrations on farms in the village, with familiar soil and climate conditions similar to those of most participants, can be effective in alleviating farmers' concerns, reducing the unpredictability and uncontrollability of new technology, increasing the predictability of the probability distribution of benefits, and promoting better uptake by surrounding farmers (TAKAHASHI et al., 2020). Beliefs about potential yields depend on first-hand and local experience, and these beliefs significantly influence learning efforts, so extension by demonstrators can be a cost-effective way to enable a wide range of smallholders to use new technologies (NAKANO et al., 2018).

The first hypothesis tested in the present study was that public agricultural extension can promote adoption of improved wheat varieties among farmers, but that there may be differences in the effects of different forms of extension (training, demonstration).

2.2 Pest and Disease Experience and Farmers' Adoption Behavior regarding Improved Varieties

Compared with new agricultural technologies, farmers have more cumulative knowledge and experience of conventional technologies, and risk-averse farmers show more activity in choosing conventional technologies (BAI et al., 2015; MORGAN et al., 2020). Personal experiences of disaster may increase the probability of subjective losses and drive farmers to actively seek to adopt risk-averse measures (BROWN et al., 2018; CAI and SONG, 2017). Sudden environmental events and experience of natural disasters have a direct impact on mental health and quality of life, and such direct experience is generally more powerful than secondary information in informing attitudes and behaviors (CLAYTON et al., 2015). Perception of disaster risk can arise from direct or indirect disaster experience, and farmers often adopt improved varieties as a good climate adaptation strategy to reduce the probability of future losses (VEETTIL et al., 2021). When expected losses are greater than the cost of adopting new technology, farmers appear to be more inclined to avoid possible risks associated with adoption.

Although public agricultural extension may be successful in terms of diffusion of technology knowledge and effectively increasing farmers' awareness, adoption of improved varieties by farmers may be influenced by factors such as scale of operation and access to credit, and the desired goals of agricultural extension may not be fully achieved (MAERTENS et al., 2021). According to the "cognitive-situational-behavioral" model, situational factors may play a role in farmers' cognition and behavior (GUO and ZHAO, 2014). Pest and disease experience is an important situational factor in farmers' agricultural production and directly influences their adoption of improved varieties, while also moderating the links between public agricultural extension and behavior. Individuals with pest and disease experience can view communication content more theoretically and critically (HONG et al., 2019), which can help increase farmers' motivation to adopt improved varieties.

The second hypothesis tested in this study was that pest and disease experience can promote adoption of improved varieties by wheat farmers and that it has a positive moderating interactive effect with public agricultural extension on farmers' adoption behavior.

3 Data and Empirical Specification

3.1 Data

The data used in this paper were obtained in a household survey conducted in 2022 in Anhui Province in central China, which has excellent natural conditions for cropping and is an important commodity grain base in China. In 2021, Anhui province had 2,846 thousand ha planted with wheat and produced around 16.7 million tons of wheat grain (CRSY, 2022).

To ensure that the questionnaire was set up scientifically and reasonably, a pre-survey was conducted and the questionnaire was modified based on issues arising. In the formal survey, a three-step stratified random sampling method was used to collect data. Combining natural conditions, economic development level, and wheat planting area, Huainan City, Huaibei City, Hefei City, and Bozhou City were selected as the survey areas. We randomly selected one sample county in each city, 2-3 townships in each county, and four villages from each township. Finally, we randomly selected 10-15 farm households in each village to represent agricultural production in that village. All sample farms were dominated by grain crops and grew wheat. To ensure authenticity and reliability of the data, face-to-face interviews were used to collect information from the selected farm households and the interviewers were all graduate students majoring in agricultural economics. The survey questionnaire mainly covered the individual characteristics of household heads, the structure of household labor force, household income, adoption status of wheat varieties, etc. Data on a total of 565 farm households were obtained, but 40 observations were eliminated due to some missing data and outliers, so the total number of households represented by the data used was 525. Definitions and descriptive statistics on the variables are shown in Table 1.

3.2 Variable Selection

3.2.1 Dependent Variable

The dependent variable in this study was adoption of improved wheat varieties by farmers. Technology adoption by farmers is generally considered to comprise two stages, namely adoption decision and adoption degree (BIRHANU et al., 2017; LI and SHEN, 2021). The survey question "Did you use improved wheat varieties in the 2021/2022 cropping season?" was used to measure adoption of improved varieties, where the adoption decision was assigned a value of one if the farmer adopted improved varieties and zero otherwise. In this study, we considered varieties bred in recent years, such as Luyan128, Yangmai33, and so on, as improved varieties. Improved varieties are more advantageous in risk management, with lower yield loss occurring in the event of pest and disease outbreaks (YITAYEW et al., 2022). We did not consider sub-generation seeds as improved varieties, because of their weak resistance (ZHENG et al., 2021). As shown in Table 1, 36.8% of the farmers surveyed indicated that they had adopted one or more improved wheat varieties. Degree of adoption was expressed as the share of area planted with improved wheat varieties, as a continuous variable. As the statistics in Table 1 show, around 28.4% of the land cropped by the farmers interviewed was planted with improved wheat varieties.

3.2.2 Independent Variable

The independent variable was public agricultural extension, which has been measured in previous studies as a discrete variable in the form of "Have you received relevant agricultural skills training?" (YANG et al., 2022). However, this ignores possible differences in the effects of frequency of extension inputs. HUANG et al. (2015) noted that the effectiveness of knowledge training may decline over time if no addi-

Table 1. Definition of variables and descriptive statistics

Variables	Definition	Mean	S.D.
Adoption decision	Whether the farmer adopted improved wheat varieties in the 2021/2022 cropping season: yes = 1; no = 0	0.368	0.483
Adoption degree	Share of area planted to improved wheat varieties	0.284	0.413
Public agricultural extension	Number of public agricultural extension events attended in the past year	1.086	1.207
Training	Participated in training: yes = 1; no = 0	0.322	0.468
Demonstration	Participated in demonstrations: yes = 1; no = 0	0.116	0.321
Pest and disease experience	Share of your wheat area that suffered pests and diseases in the last cropping season	0.101	0.230
Gender	Gender of household head: male = 1; female = 0	0.789	0.409
Age	Age of household head (years)	53.718	11.345
Education	Years of education of household head (years)	7.941	3.986
Years in farming	Years in farming (year)	30.571	14.724
Agricultural labor	Number of agricultural laborers	2.116	0.947
Share of aging agricultural labor	Share of agricultural labor over 60 years of age (%)	0.241	0.400
Total household income	Total household income in 2021 (10,000 EUR[1])	1.686	2.761
Share of agricultural income	Share of agricultural income in total income	0.556	0.354
Debt	Whether the household has debts: yes = 1; no = 0	0.347	0.476
Land scale	Total household land area for wheat production (ha)	8.261	16.919
Rent-in land	Area of rent-in land for wheat production (ha)	6.940	15.963
Land plots	Number of plots of land	20.327	49.662
Irrigation availability	Share of land area that can be irrigated	0.938	0.186
Private extension	Obtain information from seed dealers: yes = 1; no = 0	0.507	0.500
Peer information sharing	Information sharing from peers: yes = 1; no = 0	0.661	0.474
Internet use	Access to information on the internet: yes = 1; no = 0	0.684	0.465
Adoption by relatives and friends	Whether more than half of relatives and friends have adopted improved varieties: yes = 1; no = 0	0.474	0.500
Regional variables			
Huainan	yes = 1; no = 0	0.202	0.402
Bozhou	yes = 1; no = 0	0.204	0.403
Hefei	yes = 1; no = 0	0.250	0.433
Huaibei	yes = 1; no = 0	0.345	0.476
Farm performance variables			
Wheat yield (ln)	Wheat yield (kg/ha)	8.857	0.214

Notes: [1]EUR 1 = CNY 7.637 in 2021
Source: own calculations

tional effort is made after the initial training. In view of this, the survey question "Number of public agricultural extension involving improved wheat varieties attended in the past year?" was used to measure public agricultural extension. Further, considering the diversity of agricultural extension methods, agricultural extension was divided into training and demonstration (HUANG et al., 2022; MARIANO et al., 2012). A value of one was assigned if any household member had participated in training provided by the public agricultural extension system, and a value of zero otherwise. Similarly, the dummy variable was set to one if a demonstration was attended, and zero otherwise. The farmers interviewed reported attending public agricultural extension events on average around 1.09 times, with 32.2% attending training events and 11.6% participating in demonstrations.

3.2.3 Moderating Variables

The moderating variable used was pest and disease experience of farmers, which can be expected to influence the utility of public agricultural extension. It was represented by the survey question "Share of your wheat area that suffered pests and diseases in the last cropping season". The survey responses indicated that the share of wheat area suffering from pests and diseases in the previous season was around 10.1% of the total area. Climate change plays a crucial role in altering various physiological and biochemical processes of wheat growth, while the interannual prevalence of major pests and diseases of wheat is also dependent on changes in climate conditions (TRIPATHI et al., 2016; SONG et al., 2019).

3.2.4 Control variables

To avoid biased estimates due to omission of important variables and with reference to existing studies (OTTER and DEUTSCH, 2023; LI and SHEN, 2021; TAKAHASHI et al., 2020), other factors that may affect adoption of technology by farmers were controlled for in this study. From among individual characteristics of household heads, we selected four variables: gender, age, education, and years of farming. There is reported to be a negative relationship between gender and adoption of agricultural technologies, with females having a greater propensity to adopt (ISSAHAKU and ABDULAI, 2020; MA and WANG, 2020). However, YU et al. (2021) found that households with a male head were more likely to adopt technologies than households with a female head. Years of farming tend to be related to age, and older farmers with extensive experience are more likely to employ traditional production technologies (OJO et al., 2021). Farmers with a higher level of education are better able to get information and find appropriate new technologies for their production (SHIFERAW et al., 2014). Analysis of the data showed that 78.9% of household heads were male, with an average age of 53.7 years, an average of 7.9 years of schooling, and around 30.6 years of farming (Table 1).

Among household characteristics, we considered agricultural labor, share of aging agricultural labor, total household income, share of agricultural income, and debt. The impact of farm household labor on adoption of agricultural technology is mixed, i.e., it can be negative or positive (YU et al., 2021; GAO et al., 2020). We predicted a similar relationship between aging labor and farm households' adoption behavior regarding improved varieties, where aging of the agricultural labor force was measured as the share of agricultural labor aged over 60 years. New technologies tend to put more financial pressure on farmers, and thus wealthier farmers are more likely to invest in improved varieties (GAO et al., 2020). Farmers' income is generally composed of both farm and nonfarm income. The higher the share of farm income in total income, the higher farmers' concern and dependence on agriculture and the higher adoption of recommended wheat varieties is likely to be (ULLAH et al., 2022). Compared with part-time farms, full-time farms have higher technological change (ADDO and SALHOFER, 2022). Of the farmers surveyed, the average household had around 2.1 agricultural laborers, 24.1% of whom were over the age of 60. In 2021, total income per household was around 16,860 EUR, of which 55.6% was from agriculture, and 34.7% of farmers reported that they had debts (Table 1).

Among land characteristics, in this study we controlled for land scale, rent-in land, land plots, and irrigation availability. Previous research has shown that new varieties are more likely to be adopted by households with larger farms (LE et al., 2020). Farmers who rent land also tend to adopt improved technologies more often and obtain a larger share of their yields from rented land (MARIANO et al., 2012). The impact of land fragmentation is two-fold, increasing production costs but also acting as a risk management strategy (WANG et al., 2020; NTIHINYURWA et al., 2019). Irrigation availability is reported to be an important physical factor influencing the use of modern varieties (MARIANO et al., 2012). In this study, we measured irrigation availability using the share of irrigable area in total land area. Analysis of the data showed that the average land area used for wheat by the participating farmers was 8.2 ha, of which the average rented-in land comprised 6.9 ha and the number of plots was 20.3 (Table 1). Of the total land farmed, 93.8% was effectively irrigated. The size of the participating farms far exceeded the average area operated by Chinese farmers, because Anhui Province encourages farmers to transfer their land. By the end of 2021, the province's land transfer rate was 52.8%, involving around 2,817 thousand ha of land.[1]

Besides public agricultural extension, farmers have other sources of information. Here we mainly considered private extension, peer information sharing, and the internet. Numerous studies have confirmed that these sources of information have an important impact on farmers' production behavior shifts (WUEPPER et al., 2021; PHAM et al., 2021; LIU et al., 2019). For example, MA and WANG (2020) found that use of the internet can help smallholders alleviate information asymmetries, promoting adoption of technology. In the sample of farmers we interviewed, 50.7% indicated that they were able to obtain relevant seed information from the private sector (e.g., seed dealers), 66.1% were able to obtain it from their peers,

[1] http://nync.ah.gov.cn/public/7021/56373541.html

and 68.4% were able to seek relevant seed information with the help of the internet.

In addition, four regional dummy variables (Huainan, Bozhou, Hefei, and Huaibei) were considered to control for spatial characteristics. A value of one was allocated if the farmer lived in the region, and a value of zero otherwise.

3.3 Empirical Model Specification

3.3.1 Heckman Selection Model

Adoption of improved wheat varieties by farmers is composed of two sequential decision-making processes: choosing whether to adopt improved varieties and deciding on the degree of adoption. Whether farmers adopt improved varieties and the degree of adoption are not random, but rather the result of their 'self-selection', which is influenced by a series of personal characteristics, family characteristics, etc. In the case of non-adoption, the degree of adoption is unobservable, i.e., the sample data are non-random in nature. If ordinary least squares (OLS) estimation is used, the estimation results may suffer from sample selection bias (WOOLDRIDGE, 2002). This problem can be effectively addressed by the Heckman selection model, which has been used previously as an effective tool to analyze farmers' behavior (QUIROGA et al., 2020; BIRHANU et al., 2017; LI and SHEN, 2021). The model introduces a two-stage process to correct for sample-induced endogeneity and to create a selection parameter (inverse Mills ratio) to account for potential sample selection bias (HECKMAN, 1979). The specific model used in the present study consisted of a selection Equation (1) and an outcome Equation (2):

$$
\begin{aligned}
&Y_{i1}^{*} = \alpha Z_i + \mu_{i1} \\
&Y_{i1} = \begin{cases} 1, if Y_{i1}^{*} > 0 \\ 0, if Y_{i1}^{*} \le 0 \end{cases}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
&Y_{i2}^{*} = \beta X_i + \mu_{i2} \\
&Y_{i2} = \begin{cases} c, if Y_{i1} = 1 \\ 0, if Y_{i1} = 0 \end{cases}
\end{aligned} \tag{2}
$$

where Y_{i1}^{*} is the latent variable and Y_{i1} and Y_{i2} are the dependent variables of the two equations, representing farmers' decision to adopt improved varieties and the degree of adoption, respectively. When $Y_{i1}^{*} > 0$, farmers adopt the improved variety, i.e., $Y_{i1} = 1$ is observed. Otherwise, farmers choose not to adopt, and X=0 is observed. Y_{i2} can be observed only when $Y_{i1} = 1$, and c is the degree of adoption of improved varieties by farmers at this time. Z_i and X_i are explanatory variables, α and β are coefficients to be estimated, and μ_{i1} and μ_{i2} represent random disturbance terms.

The conditional expectation of the degree of adoption of improved wheat varieties by farmers in the outcome Equation is:

$$
\begin{aligned}
&E(Y_{i2} \mid Y_{i2} = c) = E(Y_{i2} \mid Y_{i1}^{*} > 0) \\
&= E(\beta X_i + \mu_{i2} \mid \alpha Z_i + \mu_{i1} > 0) \\
&= E(\beta X_i + \mu_{i2} \mid \mu_{i1} > -\alpha Z_i) \\
&= \beta X_i + E(\mu_{i2} \mid \mu_{i1} > -\alpha Z_i) \\
&= \beta X_i + \rho\sigma\lambda(-\alpha Z_i)
\end{aligned} \tag{3}
$$

where $\lambda(-\alpha Z_i)$ is the inverse Mills ratio, σ is the standard deviation, and ρ is the correlation coefficient of Y_1 and Y_2. If $\rho \ne 0$, then the selection of Y_1 has an effect on Y_2, i.e., there is a selection bias. If $\rho = 0$, then estimation using the OLS model is valid.

It should be noted that to ensure that Equation (1) is identifiable and to avoid the problem of multicollinearity, in variable setting it is necessary to introduce at least one variable satisfying the exclusivity condition that affects farmers' adoption decisions, but not the degree of adoption, i.e., X_i must be a subset of Z_i (WOOLDRIDGE, 2002). In this study, adoption by relatives and friends ("Whether more than half of relatives and friends have adopted improved varieties?") was selected as the exclusion restriction variable. Farmers are not independent actors, and behavioral decisions among friends and relatives are mutually influenced (MA and WANG, 2022). At the same time, farmers are risk-averse and diffusion of technology is difficult to achieve overnight, so adoption by friends and relatives would not affect the degree of adoption by farmers (YU et al., 2021; ROGERS, 1983).

Considering the problem of possible causal endogeneity between public agricultural extension and adoption of improved varieties by farmers, in this study we used a two-stage least squares (2SLS) test (Table 2). Drawing on KATENGEZA et al. (2019), special status (whether any member of the household is a village cadre or party member) was selected as the instrumental variable. Farmers with special status were found to be more likely to access public agricultural extension, but this did not affect their adoption of improved varieties. The regression results showed that the first-stage regression F-value was greater than the critical value (Table 2), so it can be concluded that there is no weak instrumental variable problem. The Durbin-Wu-Hausman (DWH) test value was 0.126, which was not statistically significant. Therefore, it can be concluded that public agricultural extension is

Table 2. Estimates obtained using the Heckman selection model

Variables	2SLS[1]	Heckman		Heckman		OLS[2]
		First	Second	First	Second	
Public agricultural extension	0.110 (0.083)	0.236*** (0.051)	0.061*** (0.020)			0.081*** (0.015)
Training				0.679*** (0.130)	-0.005 (0.054)	
Demonstration				1.073*** (0.200)	0.204*** (0.070)	
Gender	0.051 (0.040)	0.214 (0.162)	0.100 (0.068)	0.210 (0.165)	0.083 (0.067)	0.053 (0.046)
Age	0.003 (0.003)	0.010 (0.010)	0.002 (0.004)	0.011 (0.010)	0.001 (0.004)	0.003 (0.003)
education	0.011** (0.006)	0.037** (0.018)	0.012* (0.007)	0.036** (0.018)	0.010 (0.007)	0.012** (0.005)
Years in farming	0.000 (0.002)	-0.001 (0.007)	0.003 (0.003)	0.002 (0.007)	0.004 (0.003)	0.000 (0.002)
Agricultural labor	-0.029 (0.018)	-0.077 (0.067)	-0.066** (0.026)	-0.083 (0.069)	-0.063** (0.026)	-0.030 (0.019)
Share of aging agricultural labor	-0.018 (0.050)	-0.161 (0.179)	0.004 (0.068)	-0.171 (0.185)	0.028 (0.067)	-0.017 (0.051)
Total household income	-0.013 (0.021)	0.077 (0.071)	-0.014 (0.025)	0.077 (0.073)	-0.012 (0.025)	0.012 (0.019)
Share of agricultural income	0.079 (0.064)	0.450** (0.204)	-0.027 (0.076)	0.576*** (0.209)	-0.008 (0.076)	0.089 (0.058)
Debt	-0.024 (0.037)	-0.204 (0.133)	0.043 (0.051)	-0.146 (0.137)	0.061 (0.049)	-0.024 (0.038)
Land scale	0.000 (0.002)	-0.003 (0.005)	0.003 (0.002)	-0.006 (0.005)	0.003 (0.002)	-0.000 (0.001)
Rent-in land	0.001 (0.001)	0.004 (0.004)	0.001 (0.001)	0.004 (0.004)	0.001 (0.001)	0.001 (0.001)
Land plots	0.001 (0.001)	0.001 (0.001)	0.000 (0.000)	0.002 (0.002)	-0.000 (0.000)	0.001 (0.000)
Irrigation availability	0.024 (0.094)	0.249 (0.341)	-0.126 (0.125)	-0.152 (0.341)	-0.212* (0.122)	0.016 (0.095)
Private extension	0.000 (0.039)	0.060 (0.134)	-0.053 (0.049)	0.009 (0.137)	-0.081* (0.048)	0.003 (0.039)
Peer information sharing	0.105*** (0.038)	0.333** (0.145)	0.137** (0.059)	0.299** (0.147)	0.122** (0.058)	0.106*** (0.041)
Internet use	0.039 (0.041)	0.153 (0.145)	0.006 (0.054)	0.087 (0.148)	-0.006 (0.052)	0.041 (0.042)
Adoption by relatives and friends		0.332*** (0.121)		0.322*** (0.125)		
Regional variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.350 (0.248)	-3.122*** (0.854)	0.424 (0.375)	-2.949*** (0.870)	0.691* (0.361)	-0.336 (0.238)
Lambda		0.158** (0.075)		0.131* (0.077)		
Log likelihood		-331.009		-313.824		
First stage F statistic	17.229					
DWH[3] value	0.126					

Notes: Significant at *10%, **5%, and ***1%. Standard error in brackets. [1]Two-stage least squares. [2]Ordinary least squares. [3]Durbin-Wu-Hausman test.

Source: own calculations

not endogenous. The lambda coefficient for the estimates from the Heckman selection model was significant at the 5% statistical level, confirming the presence of selection bias in the sample and indicating that use of the Heckman selection model was appropriate.

3.3.2 Endogenous Switching Regression Model

In observational studies, farmers' decision-making behavior may be influenced by certain factors. To control for this problem, the propensity score matching (PSM) model has been widely used in various types of studies (BAMBIO et al., 2022; ZHANG et al., 2020; AMADU et al., 2020). However, the PSM model only considers the selection bias of observable variables and ignores the possible bias caused by unobservable factors. In contrast, the ESR model not only eliminates the selection bias caused by observable and unobservable factors, but also fits the determination equation of farm performance and its counterfactual equation, which compensates for the shortcomings of the PSM model (BAIRAGI et al., 2021; HUANG et al., 2022). Therefore, we used the ESR model to assess the impact of adoption of improved wheat varieties by farmers with the following model equations:

Selection equation (whether the farmer adopted improved varieties or not):

$$New_i = \gamma x_i + k_i I_i + \mu_i \tag{4}$$

Outcome Equation 1 (treatment group, farm performance of adopting improved varieties):

$$Y_{i1} = \beta_{i1} X_{i1} + \sigma_{\mu 1}\lambda_{i1} + \varepsilon_{i1}\text{, if } Improved_i = 1 \tag{5}$$

Outcome Equation 2 (control group, farm performance without adoption of improved varieties):

$$Y_{i0} = \beta_{i0} X_{i0} + \sigma_{\mu 0}\lambda_{i0} + \varepsilon_{i0}\text{, if } Improved = 0 \tag{6}$$

where $Improved_i$ represents whether the farmer adopted improved varieties or not, x_i represents the factors influencing the farmer's decision to adopt improved varieties, I_i is the instrumental variable, Y_{i1} and Y_{i0} represent farm performance on adopting improved varieties and not, respectively, X_i represents the factors influencing farm performance, λ_{i1} and λ_{i0} are the inverse Mills ratio, introduced in this study together with their covariances $\sigma_{\mu 1} = \mathrm{cov}(\mu_i, \varepsilon_{i1})$ and $\sigma_{\mu 0} = \mathrm{cov}(\mu_i, \varepsilon_{i0})$ to address the problem of possible self-selection bias caused by unobservable factors (where μ_i is the error term of the selection equation, and ε_{i1} and ε_{i0} are the error terms of the outcome Equations (1) and (2), respectively), and γ, k_i, β_{i1}, and β_{i0} are the coefficients to be estimated using the full information great likelihood method.

In this study, the treatment effect of adoption of improved wheat varieties on farm performance was of interest, and therefore we needed to estimate the average treatment effect of the treated (ATT):
Expectations for farm performance of adoption (observed):

$$E[Y_{i1} | New_i = 1] = \beta_{i1} X_{i1} + \sigma_{\mu 1}\lambda_{i1} \tag{7}$$

Expectations for non-adopted farm performance (counterfactual):

$$E[Y_{i0} | New_i = 1] = \beta_{i0} X_{i1} + \sigma_{\mu 0}\lambda_{i1} \tag{8}$$

The ATT of adopting on farm performance was then estimated as the difference between Equations (7) and (8):

$$\begin{aligned} ATT &= E[Y_{i1} | New_i = 1] - E[Y_{i0} | New_i = 1] \\ &= (\beta_{i1} - \beta_{i0}) X_{i1} + (\sigma_{\mu 1} - \sigma_{\mu 0})\lambda_{i1} \end{aligned} \tag{9}$$

4 Results and Discussion

4.1 Estimated Impact of Public Agricultural Extension on Farmers' Decision to Adopt Improved Wheat Varieties

The estimates produced by the Heckman selection model are presented in Table 2, together with the OLS estimates for comparison. The results of Heckman's first-stage Probit selection model showed that the coefficient of public agricultural extension was positive and significant at the 1% statistical level (column 4 in Table 2), indicating that the more public agricultural extension farmers received, the higher the probability of them adopting improved wheat varieties. This is similar to findings by BAMBIO et al. (2022) that increased exposure of farm households to new technologies can increase the adoption rate of improved seeds. Inefficient information is a barrier to adoption in developing countries, and public agricultural extension aims to overcome this barrier (OGUTU et al., 2020).

Regarding the two different forms of extension studied (column 6 in Table 2), the coefficients for training and demonstration were all positively significant at the 1% statistical level, which indicates that both training and demonstration approaches can significantly increase the likelihood of farmers adopting improved wheat varieties. This is similar to findings in previous studies (YU et al., 2023; MARIANO et al., 2012). However, some contradictory findings exist. For example, PAN et al. (2017) found that traditional one-time training methods had little impact in reducing fertilizer use, while RAGASA (2020) found that only 13% of farmers in Malawi benefited through leading farmers, with limited implementation and effectiveness.

Among the control variables studied (column 4 in Table 2), education, share of agricultural income, and peer information sharing had a significant positive effect on farmers' decision to adopt. Education has been identified in previous studies as an important factor influencing farmers' behavior. RUZZANTE et al. (2021) found that farmers' education level was strongly associated with adoption of agricultural technologies such as improved varieties. Farmers with higher education tend to have easier access to information and benefit more from technology (BIRHANU et al., 2017; CECI et al., 2021).

The coefficient for the share of agricultural income was positive and statistically significant (Table 2), suggesting that farmers with a high share of total household income from agriculture were more likely to adopt improved wheat varieties to secure household income. This is similar to findings by CAI et al. (2022). However, KILIC et al. (2009) argued that unless more favorable conditions are created, farmers are less likely to invest their off-farm income in agriculture.

Peer information sharing had a significant positive effect on farmers' decision to adopt (Table 2), indicating that farmers who regularly shared agricultural information or experiences with each other were more likely to adopt improved wheat varieties than other peers. This is similar to the finding by PHAM et al. (2021) that information sharing among neighbors and friends plays an important role in encouraging the spread of agricultural technology. Experience and information from social networks can accelerate adoption of technology by marginal farmers (NAZLI and SMALE, 2016).

The coefficient of the exclusion restriction variable was positive and significant at the 1% statistical level (column 4 in Table 2), indicating that the probability of adoption was higher for farmers whose relatives and friends had already adopted the improved variety. In rural China, farmers come from the same (or several same) patrilineal ancestors and live geographically close to each other (FOLTZ et al., 2020). Thus, it is very common for farmers to be familiar with each other, trust each other, and learn from their neighbors (ZHENG and LUO, 2022; ZHENG et al., 2021; TIRKASO and HAILU, 2022).

4.2 Estimated Impact of Public Agricultural Extension on Degree of Adoption of Improved Wheat Varieties by Farmers

In the second stage of the Heckman selection model, we investigated the determinants of degree of adoption of improved wheat varieties by farmers. The inverse Mills ratio from the first-stage selection model was used as an explanatory variable to control for the effect of selection bias in estimating the parameters. The results obtained (see column 5 in Table 2) showed that the coefficient of public agricultural extension was significantly positive at the 1% statistical level, which indicates that public agricultural extension can enhance the degree of adoption of improved wheat varieties by farmers. This is similar to findings by ZAKARIA et al. (2020) and MGENDI et al. (2022). A possible explanation is that the greater the number of agricultural extension events in which farmers participate, the better the information they have and the less they need to worry about loss of benefits due to lack of information, thus enhancing the intensity of adoption of improved varieties (OGUTU et al., 2020; YITAYEW et al., 2021).

For the two different forms of extension tested, the coefficient for demonstration was statistically significant at the 1% level and the coefficient for training was not significant (column 7 in Table 2). This indicates that farmers who had participated in demonstrations had a higher degree of adoption of improved wheat varieties, while training had no obvious effect. MAERTENS et al. (2021) noted that different agricultural extension approaches can differ significantly in terms of time, cost, and farmer learning. Receiving training has been found not to be effective in reducing the area planted with older varieties by farmers (TAYLOR and BHASME, 2018; BAI et al., 2015).

Analysis of control variables showed that the degree of adoption of improved wheat varieties by farmers was mainly influenced by education, agricultural labor, and peer information sharing. There was a significant negative relationship between agricultural labor and degree of adoption, i.e., the more abundant agricultural labor, the lower the degree of adoption of improved varieties. This is similar to results reported by MARIANO et al. (2012), who found a negative relationship between household size and certified seed technology adoption. In contrast, BAI et al. (2015) concluded that increasing household size favored an increase in the number of varieties grown.

Both education and peer information sharing had a significant positive effect on degree of adoption, indicating that information sharing among peers can increase the proportion of improved wheat varieties planted. A possible explanation is that education enhances farmers' personal competence and that peer-to-peer interaction builds trust (TRAN-NAM and TIET, 2022; LIU et al., 2019), which acts as an 'enhancer' for degree of adoption of improved wheat varieties by farmers.

4.3 Robustness Test

To test the robustness of the estimation results, two different tests were performed. In the first robustness test, the sub-sample of farmers aged over 70 years old was excluded. The reason for this is that older farmers may have more agricultural experience or relatively poor technology adoption ability, and that scarcity of public agricultural extension service resources favors progressive and capable farmers (ADAMS et al., 2021; YANG et al., 2022). The results obtained (Table 3) showed that the lambda coefficient was significant, indicating that use of the Heckman selection model was appropriate. Public agricultural extension had a positive effect on farmers' decision to adopt improved seeds and on degree of adoption (both statistically significant at the 1% level). This is consistent with the results in Table 2 and indicates robustness of those results.

In the second robustness test, based on LI and SHEN (2021), the Probit and Tobit models were used to explore the effect of public agricultural extension on adoption of improved wheat varieties by farmers. The coefficients of public agricultural extension were found to be significantly positive in both the Probit and Tobit models (Table 3), again indicating good robustness of the estimates obtained with the Heckman selection model.

Table 3. Results of robustness tests

Variables	Heckman		Probit	Tobit
	First	Second		
Public agricultural extension	0.243*** (0.054)	0.064*** (0.022)	0.247*** (0.051)	0.191*** (0.036)
Adoption by relatives and friends	0.274** (0.131)			
Control variables	Yes	Yes	Yes	Yes
Regional variables	Yes	Yes	Yes	Yes
Constant	-2.900*** (0.908)	0.501 (0.400)	-3.084 (0.844)	-2.174*** (0.636)
Lambda	0.145* (0.086)			
Log likelihood	-305.195		-309.776	-418.927

Notes: Significant at *10%, **5%, and ***1%. Standard error in brackets.
Source: own calculations

4.4 Moderating Effects of Pest and Disease Experience

Within the theoretical framework developed in this study, we introduced pest and disease experience and its interaction with public agricultural extension into the Heckman selection model, in order to further test the utility of pest and disease experience on the outcomes of public agricultural extension in promoting adoption of improved wheat varieties. In first-stage estimation by the Heckman model (Table 4), the coefficient of pest and disease experience was positively significant at the 1% statistical level, indicating that farmers whose crops had suffered from pests and diseases were more likely to adopt improved varieties. The coefficient of the interaction term between pest and disease experience and public agricultural extension was significantly positive at the 5% statistical level, indicating that pest and disease experience had a positive moderating effect on outcomes of public agricultural extension work relating to farmers' adoption decisions on wheat. Although public agricultural extension can help farmers overcome information barriers to technology adoption, some farmers are still likely to choose familiar technologies due to risk aversion (BAI et al., 2015; MORGAN et al., 2020). Knowledge of improved varieties as a common climate adaptation strategy, combined with cropping disaster experience, increases the likelihood of adoption (KATENGEZA et al., 2019). Thus, farmers' pest and disease experience can increase the probability of them deciding to adopt improved varieties and play a positive moderating role in the relationship between public agricultural extension and farmers' adoption decisions.

In second-stage estimation by the Heckman model, the coefficients of pest and disease experience and its interaction term with public agricultural extension were not significant (Table 4), indicating that experience did not increase the area of improved varieties grown by farmers and had no significant moderating effect. A possible explanation for this unexpected finding is that extension advice often does not take into account price risk or spatial heterogeneity of farmers'

Table 4. Moderating effects of pest and disease experience on adoption of improved wheat varieties by farmers

Variables	Heckman First	Heckman Second	Heckman First	Heckman Second
Public agricultural extension			0.253*** (0.051)	0.063*** (0.020)
Pest and disease experience	0.678*** (0.253)	0.080 (0.094)	0.820*** (0.271)	0.142 (0.098)
Public agricultural extension × Pest and disease experience			0.544** (0.251)	-0.109 (0.074)
Adoption by relatives and friends	0.366*** (0.116)		0.321*** (0.122)	
Control variables	Yes	Yes	Yes	Yes
Regional variables	Yes	Yes	Yes	Yes
Constant	-2.802*** (0.839)	0.533 (0.370)	-3.164*** (0.862)	0.448 (0.370)
lambda	0.172** (0.075)		0.164** (0.075)	
Log likelihood	-341.657		-322.165	

Notes: Significant at *10%, **5%, and ***1%. Standard error in brackets.
Source: own calculations.

growing conditions, while future natural disasters are difficult to predict, so farmers are slow to change seed inputs (LI, 2023; OYINBO et al., 2022). NAZLI and SMALE (2016) pointed out that variety replacement is a gradual process that tends to start with a small area of planting and is characterized by a lag. In the present study, the form of disaster considered was exposure to pests and diseases in the previous cropping season, so farmers' experience of this did not perform as expected.

4.5 Impact of Adoption of Improved Wheat Varieties on Production Performance

It is well-documented that adoption of improved agricultural technology in general can improve farm performance (TAKAHASHI et al., 2020; ZHENG et al., 2021), and adoption of improved crop varieties is no exception. In this study, we used yield of wheat to measure the impact on farm performance of improved agricultural technologies, drawing on studies by NAKANO et al. (2018) and AMADU et al. (2020). In the ESR model, we chose adoption by relatives and friends as the instrumental variable, which was found to be correlated with farmers' adoption decisions on improved varieties (see previous section), while it did not directly affect wheat yields. Therefore, use of relative/friend adoption as an instrumental variable was valid. It should be noted that all yields considered here were yields of improved varieties. For farmers who planted more than one improved variety, we used the average of their yields.

The results showed that the ATT of improved varieties on wheat yield was significant at the 1% statistical level (Table 5). The counterfactual hypothesis was that wheat yield would have been 337.83 kg/*ha* lower if the farmer had not adopted the improved variety. To verify the robustness of the results, we replaced the model and tested it again using the PSM model, which also gave a statistically significant ATT value. The estimation results from the selection equation and outcome equation of the ESR model are shown in Appendix A.

5 Policy Implications

This study revealed effects of public agricultural extension and of pest and disease experience on adoption of improved wheat varieties by farmers, and an effect of improved varieties on wheat yield. These results have important policy implications for China and other developing countries seeking to promote diffusion of improved varieties and ensure food security. Because of the important role played by public agricultural extension, government should devote more resources to this service. Considering the differences found in this study between forms of extension, particular attention needs to be paid to holding demonstrations and encouraging farmers to participate in technical training and to become demonstration households.

Agricultural extension services can also be provided by the private sector, to increase access. The

Table 5. Impact of improved wheat varieties on yield according to ESR model

Outcome by estimation technique	Adopters' yield (ln)	Non-adopters' yield (ln)	ATT[1]	T value	Change[2] (kg/ha)
ESR	8.883	8.835	0.048	3.22	337.832
PSM[3]	8.882	8.829	0.053	2.49	371.722

Notes: Significant at *10%, **5%, and ***1%. Standard error in brackets. [1]Average treatment effect of the treated. [2]The change is obtained by restoring the logarithmic form of the yields (adopters and non-adopters) in the table. [3]The result we report is the kernel matching method estimation.
Source: own calculations

survey data showed that only 32.2% and 11.6% of farmers had participated in training and demonstration activities, respectively, indicating that the public agricultural extension system in the study region seems to have insufficient capacity to provide timely services to all farmers. Diversified extension services would promote flexibility, better meet the diverse technology needs of farmers, and reduce the budget burden on the government. However, the service offering must be closely monitored and evaluated to ensure that the private sector does not focus solely on commercial farmers.

Information on risks posed by climate change to agricultural production should be provided to farmers through various channels. Improved seasonal weather forecasting is also necessary, as most weather forecasts cover only the next few days, which is too short a time frame for farmers to adjust variety inputs in a scientific and timely manner.

6 Conclusions

Seeds are the ‘silicon chips’ of development in crop production, and the introduction of improved varieties has dramatically increased food production worldwide. However, adoption of improved varieties is still not satisfactory in many developing countries, and the effectiveness of public agricultural extension in this regard is unclear. To address this issue, we analyzed the impact of public agricultural extension on adoption of improved varieties by farmers, using survey data on 525 wheat farmers in Anhui Province, China, in 2021. We also included farmers’ pest and disease experience in the analytical framework. We applied the Heckman selection model to conduct the empirical analysis and explored differences in the effects of two different forms of extension (training and demonstration). We applied the ESR model to measure the impact of improved wheat varieties on farm performance.

The results confirmed the effectiveness of public agricultural extension in promoting adoption behavior regarding improved varieties, but revealed differences between the two forms of extension. Participation in demonstrations increased the likelihood of adoption of improved varieties by farmers and also increased the proportion of acreage planted, while training had a significant positive effect only on farmers’ adoption decisions. Other important socioeconomic factors (education, agricultural labor, share of agricultural income, peer information sharing) variously helped or hindered farmers in adoption of improved varieties.

Farmers’ pest and disease experience had a facilitating effect on their decision to adopt improved varieties and positively moderated the outcomes of public agricultural extension efforts promoting adoption of improved wheat varieties, i.e., previous experience of pests and diseases by farmers improved the effectiveness of public agricultural extension in increasing adoption of improved wheat varieties by farmers. Interestingly, however, pest and disease experience did not play the expected role in degree of adoption.

Adoption of improved varieties resulted in an increase in wheat yields and improved farm performance, as farmers who adopted improved varieties would have had around 337.83 kg/ha lower wheat yield without adoption. Estimates obtained using the PSM model validated the robustness of this finding.

Several limitations in this study need to be highlighted. We used cross-sectional data, ignoring the problem of lags in adoption of improved varieties by farmers, which may have caused bias in the estimation results. In assessment of improved varieties on farm performance, profits were not assessed, due to data limitations. We also only considered pests and diseases in general, while the response behavior of farmers to specific pests and diseases may differ. We found a stronger effect of family and friends than of public agricultural extension on adoption decisions, a very interesting finding that we will explore further in future specific investigations. Overall, this study provided novel insights into the impact of pest and disease experience and public agricultural extension on adoption of improved wheat varieties by farmers, and demonstrated a positive effect of improved varieties on wheat yield.

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Appendix

Table A1. Determinants of adoption of improved varieties by farmers and its impact on wheat yield

Variables	Selection equation	Outcome equation	
		Adopted farmers	Non-adopted farmers
Gender	0.219 (0.160)	0.037 (0.042)	-0.002 (0.023)
Age	0.009 (0.009)	-0.000 (0.002)	-0.003** (0.0015)
Education	0.043** (0.017)	0.010** (0.005)	0.002 (0.002)
Years in farming	0.002 (0.007)	0.002 (0.002)	0.004*** (0.001)
Agricultural labor	-0.075 (0.066)	-0.010 (0.016)	0.001 (0.010)
Share of aging agricultural labor	-0.139 (0.176)	-0.003 (0.043)	-0.052* (0.027)
Total household income	0.065 (0.069)	0.040** (0.016)	0.013 (0.010)
Share of agricultural income	0.523*** (0.199)	0.062 (0.048)	0.001 (0.034)
Debt	-0.165 (0.131)	-0.011 (0.032)	-0.023 (0.021)
Land scale	-0.002 (0.005)	-0.002** (0.001)	-0.001 (0.001)
Rent-in land	0.006* (0.004)	0.001 (0.001)	-0.001 (0.001)
Land plots	0.002 (0.001)	-0.000 (0.000)	0.000 (0.000)
Irrigation availability	0.168 (0.328)	-0.011 (0.077)	0.042 (0.049)
Private extension	0.077 (0.131)	0.028 (0.031)	0.013 (0.021)
Peer information sharing	0.309** (0.142)	0.007 (0.037)	0.028 (0.022)
Internet use	0.157 (0.143)	-0.016 (0.034)	0.033 (0.023)
Adoption by relatives and friends	0.323*** (0.107)		
Regional variables	Yes	Yes	Yes
Constant	-2.825*** (0.833)	8.294*** (0.231)	8.747*** (0.128)
lnσ1		-1.604*** (0.123)	
ρ1		0.870*** (0.297)	
lnσ0			-1.804*** (0.039)
ρ0			-0.031 (0.309)
LR test of independent equations	4.14**		
Log likelihood	-116.024		

Notes: Significant at *10%, **5%, and ***1%. Standard error in brackets.
Source: own calculations