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Can technology demonstration promote rural households' adoption of conservation tillage in China?

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ABSTRACT

Under the uncertainty of conservation tillage on output, technology demonstration, as an information disclosure mechanism, is very worthy of attention for its effects on rural households' conservation tillage adoption. This study constructs a three-stage technology adoption model to discuss the theoretical relationship between technology demonstration and rural households' conservation tillage adoption decision, and then empirical analyzed it using a sampling rural household data from six provinces in the main grain-producing areas of China. The results show that: First, the cognition of conservation tillage is the pre-determined stage for the adoption and its intensity. Second, technology demonstration has significant positive effect on rural households' cognition of conservation tillage, but it strongly negative related to the adoption and adoption intensity. Third, extending the technology demonstration time cannot change the rural households' adoption decision. Fourth, the technological demonstration has similar effects on the conservation tillage adoption of small-scale and large-scale farmers. Fifth, increasing land size helps rural households to adopt conservation tillage, while land fragmentation hinders their adoption.

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1. Introduction

'Storing grain in the land' is the most important strategy for China to ensure crop production capacity and guarantee food security (Li et al., 2017), and conservation tillage (CT) is the key measure for it. As an environmentally friendly farming technology (Gao 2007), CT first appeared in the United States in the 1930s (Cao & Zhang, 2008), and was widely used in many countries around the world, especially in developed countries. In 2011, the total area of land adopting CT had reached 125 million hectares, 9% of the total cultivated land in the world (Kassam et al., 2014). Although China has been promoting CT since 2002, it has not been widely adopted

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by rural households (RHs). By 2014, its area of adoption accounted for only 6.4 percent of the total cultivated land area, which was significantly lower than the global average level (Li et al., 2017). Facing the national strategic needs of storing grain in the land, it is more urgent to investigate the key determinants of CT adoption, and to break the plight of the slow progress of its promotion in China. For those countries with similar problems, the findings of this study will have important value.

RHs are the major producers in Chinese agriculture sector. Their technology adoption behaviors directly determine the diffusion and application of new technologies in agriculture (Somda et al., 2002), and also relate to the application of CT. Therefore, in order to explore the main obstacles to the extension and application of CT in China, it is necessary to analyze the theoretical mechanism of RHs' technology adoption behavior and investigate the key factors affecting their adoption decisions. In the existing researches, the role of the RHs head's human capital and demographic characteristics, household employment status, land size and fragmentation degree, government subsidies on CT adoption in China have been deeply studied (Jiang et al., 2018; Tong & Liu, 2018; Wang et al., 2009, 2017; Zhu et al., 2015). However, for RHs with strong risk aversion attitudes, the uncertainty of net revenue and the cognition of a new technology is important to their adoption of this new technology. And this less discussed in previous studies.

Technology demonstration is the main channel of information supply on agricultural technologies (Kurkalova et al., 2006) and is also the most intuitive way for RHs to obtain technical information (Knowler, 2015). When RHs are surrounded by CT technology demonstration sites, it actually establishes an effective and continuous source of information dissemination, which can improve RHs' understanding of CT's effects and characteristics, lower their cognitive bias towards CT, reduce their uncertainty in revenue expectations, and then influence their adoption decisions. In terms of the behavioral logic, whether RHs adopt a technology depends first on their cognition of this technology, i.e., whether they know the technology, whether they understand its content and characteristics, and whether they are aware of its risks clearly. Only after they have full understanding of this new technology, they decide whether to adopt it and how much adopt. Therefore, as Atanu et al. (1994) pointed out, technology adoption decision is essentially a three-stage process. In the existing studies of CT adoption, a logit model or a Heckman two-stage model is used to analyze and all ignore the RHs' technology cognition, and this omission then leads to biased results due to the simultaneous errors and sample selection bias. Based on this, we introduce technology demonstration as the way of technology information supply into the RHs' CT adoption decision, and explores the role of technology demonstration with a three-stage technology adoption model (3S-TAM) in this study.

The remainder is arranged as follows: Section 2 is a brief literature review; Section 3 outlines the data and methodology, including the theoretical framework of the CT adoption decision, empirical model and data description; Section 4 reports the estimated results and Section 5 provides the conclusions and policy implications.

2. Literature review

The existing research on CT has focused on four main themes. The first is to assess the resource and environmental-ecological effects of CT applications. In terms of sustainable use of natural resources such as soil and water, studies have found that CT technology can reduce water consumption (Kumara et al., 2020) and can improve water use efficiency (Peng et al., 2020); it can reduce soil erosion by increasing soil water infiltration and reducing runoff (Han et al., 2018); and it can alter soil organic matter composition and degradation processes (Gao et al., 2021), increase organic carbon accumulation (Zhang et al., 2022), reduce soil nitrogen loss (Zhang et al., 2020), and then improve soil fertility (Peixoto et al., 2020; Yang et al., 2022) and drought tolerance (Gai et al., 2019). In terms of the impacts on soil micro-ecosystem, long-term use of CT technology was found to improve soil physical properties (e.g., soil structure, bulk density, pore size), reduce soil aggregate stability (Chimsah et al., 2020; Peixoto et al., 2020), increase soil moisture (Li et al., 2022), and reduce agricultural greenhouse gas (GHG) emissions (Awada et al., 2014; Guo et al., 2021; Salamanca-Fresno et al., 2022).

Second, the effect of CT technology on crop yield was examined. It was found that the adoption of CT technology can improve the technical efficiency of grain production (Cui et al., 2021), which can increase crop yields (Akter et al., 2021; Deines et al., 2019; Huang et al., 2021; Li et al., 2017). However, it has also been found that the effect of CT technology on crop yield is uncertain and depends on the ecological context. For example, Li et al. (2022) found that the yield effect of CT varied greatly under different representative concentration pathway scenarios (RCPs). Under RCP 4.5, the average yield of plots with CT technology application decreased; however, it increased under RCP 8.5. Zhang et al. (2022) found that CT technology could reduce maize yield, but under good hydrothermal conditions (i.e., GSP $>$ 650 mm or GST $>$ 23 °C), it resulted in an increase in maize yield.

Third, the impact of CT technology application on adopters' economic welfare such as income is analyzed. The long-term use of CT technology can reduce soil erosion, improve water retention capacity of cropland, enhance cropland quality and reduce cropland cultivation expenditures (Harper et al., 2018). Therefore, long-term adoption of CT can increase farmers' income (Deines et al., 2019; Si et al., 2021). However, some studies also found that the enhancing effect of CT adopting in isolation on farmers' income was not significant while it was notable when CT was adopted in combination with bio-diversification (Nazu et al., 2022).

Fourth, the adoption decision of CT and its determinants are explored. In such studies, the effects of individual-level factors like adopters' human capital, social capital, personal preferences, farming experience, value perceptions, risk perceptions, environmental and health awareness, household-level factors like RHs' off-farm employment status, cropland size, degree of cropland fragmentation and resource endowment, and government and social-level factors like agricultural technology training, policy subsidies and agricultural technology extension have been discussed more (Bavorová et al., 2020; Fei et al., 2019; Guo et al., 2022; Han et al., 2018; Jiang et al., 2018; Kalinda et al., 2017; Liu et al., 2021; Mao et al., 2021; Tong & Liu, 2018; Wang et al., 2017, 2021; Yoder et al., 2021). However, as pointed out by Cognition

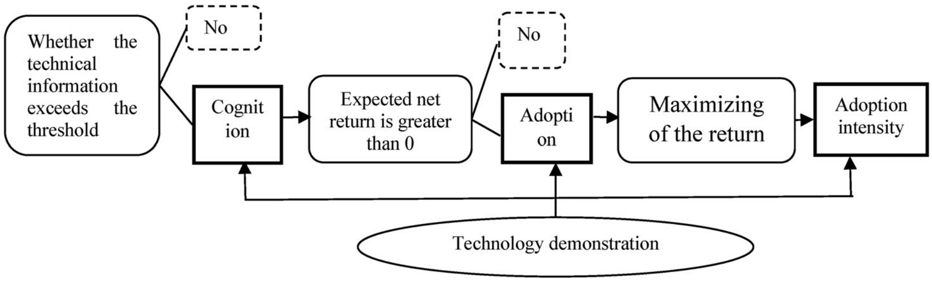

Figure 1. Technology demonstration and RHs' CT adoption decision.
Source: Author's analyzing.

and Behavior Theory, whether agricultural producers adopt CT technology depends first on their technology cognition, i.e., their knowledge and mastery of CT. Only after they have a more adequate understanding of CT, they may go on to decide whether to use CT and decide to what intensity the CT will be used. The presence of technology demonstrations as an important source of information about agricultural technologies significantly affects agricultural producers' technology cognition, which in turn affects adoption decisions through cognition. In the existing studies of CT adoption, only a few papers have explored the impact of technology demonstration (Han et al., 2018), and all of them ignore the intrinsic mechanism through which technology demonstration affects technology cognition and thus plays a role in technology decisions, which may ultimately lead to unrobust results.

Based on this, this study attempts to introduce the technology demonstration as an important determinant of CT adoption and include the cognition of CT as a new stage of CT adoption, and then build a 3S-TAM to analyze RHs' CT adoption behaviors.

3. Data and methodology

3.1. Theoretical framework: 3S-TAM

In an objective environment with insufficient information, individuals firstly need to collect, screen and identify the effective information needed for decision-making, and then form individual cognition of target object on the obtained information, and finally make decision according to the cognitive results (Somda et al., 2002). However, the information supply environment that individual decision-making faces is sharply varied, and this variation may play a role in the entire decision process through the recognition of target object. In the decision-making process of RHs' CT adoption, the setting of technology demonstration sites will increase the effective supply of information about technology costs and benefits, which can alleviate the output uncertainty faced by RHs in decision-making, and then affect technology adoption and its intensity through technology cognition. Therefore, we extend the theoretical framework raised by Somda et al. (2002) and build a 3S-TAM shown as Figure 1.

Specifically, the first stage is defined as technology cognition (i.e., whether hear about the CT), the second stage is defined as the adoption decision (i.e., whether to adopt CT), and the third stage is defined as the adoption intensity decision (i.e., how much CT to adopt). In the first stage, RHs form technology cognition based on the local diffusion degree of the CT information and their cognitive ability. Before their technology cognition reach a certain threshold level, they do not move to the second 'whether to adopt' stage. In the second stage, RHs who hear about the CT make the decision to adopt CT by comparing the net return from adoption versus non-adoption. And only if the net return from adoption is greater than that of non-adoption, RHs would adopt the CT and then move to the third stage. In the third stage, the RHs decide how much to adopt based on the maximization of return. In the following, we bring out a detail illustration of these three stages.

Stage 1: Cognition of CT

Cognition refers to the processes of acquiring and applying knowledge or information processing (Zheng et al., 2012). The RHs' cognition of CT depends on the amount of information they obtain (inf^*). If the RHs' information amount inf^* exceeds a certain threshold value (inf_0), effective cognition of CT will be formed (Saha et al., 1994). Therefore, the occurrence of RHs' technical cognition should be satisfied with the conditions as Equation (1):

$$inf^* > inf_0 \tag{1}$$

And the amount of CT information that RHs can obtain is usually determined by the information supply environment that they face and their own cognitive ability. CT demonstrations can improve the information supply environment and increase the information supply quantity of CT. Given RHs' cognitive ability, it can promote the RHs' information acquisition, thereby helping they to form more effective cognition of CT. Therefore, we proposed

Hypothesis 1: technology demonstration has a positive effect on RHs' cognition of CT.

Stage 2: CT adoption decision

The rational RHs pursue the maximization of planting profit (π_{crop}), and guide with this goal, they make a decision to adopt CT. If the land area of a RH using the conventional tillage is A_1 and the area using CT is A_2, the total land size he planted is $A = A_1 + A_2$. If $A_2 = 0$, this means the RH did not adopt CT, and $A_2 > 0$ indicates he adopted CT. Assuming the products from the plots of land that adopt conventional tillage and CT are of the same quality and price, then the expected profit is determined by Equation (2):

$$\underset{inf^*}{E}(\pi_{crop}) = \underset{inf^*}{E}\left[p \cdot \{f(A_1) + g(A_2)\tilde{e}\} - c_1 \cdot (A_1 + A_2\big) - c_2\tilde{e} \cdot \mathrm{A}_2\right] \tag{2}$$

In Equation (2), $E\ inf^*(\pi_{crop})$ is the RH's expected planting profit where the acquired CT information is inf^*, p is the unit price of the product and $f(A_1)$ is the yield of land (A_1) using conventional tillage, $g(A_2)\tilde{e}$ is the yield of land (A_2) using

CT, $f(A_1) + g(A_2)\tilde{e}$ is the total yield, c_1 is the unit cost of conventional tillage and $c_2\tilde{e}$ is the additional unit cost of CT (e.g., additional costs for machinery, labor, etc.). Due to long-term use, the unit yield and cost of cultivated land using conventional tillage are known for each RH and are certain. However, for land using CT, due to uncertainties of technology and risks, the additional unit field and cost are affected by the random variable ($\tilde{e}$). The $\tilde{e}$ is the expectation of RHs on the field and cost change from adopted CT, which closely related to the acquired information level (inf^*). Expected profit maximization requires Equation (2) to satisfy the following first-order conditions:

$$\underset{inf^*}{E}\left\{p \cdot f'(A_1) - c_1\right\} = 0 \tag{3a}$$

$$\underset{inf^*}{E}\left\{p \cdot g'(A_2)\tilde{e} - (c_1 + c_2\tilde{e})\right\} = 0 \tag{3b}$$

From Equations (3a) to (3b), it can be seen that the decision of RHs to adopt conventional tillage and CT is separable, and the optimal operating area (A_1^*) using conventional tillage is only related to the certain product price (p) and production cost (c_1). However, the optimal land area (A_2^*) using CT is not only related to these certain price (p) and cost (c_1), but also to the additional production cost (c_2) and the random variable ($\tilde{e}$). Since the decision is separable, this means that whether RHs adopt CT or not only need to consider the condition of Equation (3b). That is, the decision of RHs to adopt CT is determined by the RHs' judgements of the relative size of marginal revenue ($p \cdot g'(A_2)\tilde{e}$) and marginal cost ($c_1 + c_2\tilde{e}$) of CT, that differentiate with the technology information level (inf^*). If $p \cdot g'(A_2)\tilde{e} > c_1 + c_2\tilde{e}$, RHs will adopt CT. Since the marginal revenue and cost of CT adoption are related to the random variable $\tilde{e}$, they are also affected by the amount of technical information (inf^*) owned by RHs. The technology demonstration can improve RHs' technical information acquisition of CT, which in turn affects RHs' judgment on the marginal net revenue of CT. If the technology demonstration helps RHs form a judgment that expected marginal net return of CT greater than 0, it will promote RHs' adoption of CT; on the contrary, If RHs' consider the expected marginal net return is equal to or less than zero, it will inhibit RHs' adoption of CT. Therefore, we proposed

> Hypothesis 2: The effect of technology demonstration on RHs' CT adoption depends on the cost and revenue information of CT obtained by RHs. Due to the net revenue of CT may be greater than 0, equal to 0, or less than 0 at different demonstration sites, the effect of technological demonstration on RHs' CT adoption is uncertain.

Stage 3: CT adoption intensity decision

From Equation (3b), we known that once the condition $p \cdot g'(A_2)\tilde{e} > c_1 + c_2\tilde{e}$ is properly satisfied, RHs will adopt CT, and determine the land size (A_2^*) with the expected marginal net revenue. If the technology information (inf^*) helps RH to form a larger net revenue expectation, the land area of CT (A_2^*) will be larger. Since this expectation is co-determined by the actual marginal net revenue of CT and the judgment of RHs on the uncertainty of output, as the amount of technical information increased, their expected net revenue will close to the actual value gradually. Therefore, in terms of the technology demonstration, even it can reduce the net revenue uncertainty of CT for RHs, the enhance effect of technology demonstration on RHs' adoption intensity of CT depends on the real revenue performance of CT in the demonstration. Therefore, we proposed

> Hypothesis 3a: The impact of technology demonstrations on RHs' CT adoption intensity decision is uncertainty as well.

With the time extension of technology demonstration, the potential long-term benefits of CT due to the land quality improvement will gradually appear, and the performance of its marginal benefit over cost will become more obvious, then

> Hypothesis 3b: In the regions with a long time CT demonstration, the positive effect of technology demonstration on CT adoption will become apparent and stronger.

3.2. Empirical model

Based on the theoretical analysis, we establish a 3SLS model that includes the RHs' CT cognition equation, CT adoption equation and CT adoption intensity equation. According to the discussion of stage 1 and Equation (1), the RHs' CT cognition (y^c) is determined by $inf^* > inf_0$. If $inf^* - inf_0 > 0$, the RHs hear about the CT; conversely, If $inf^* - inf_0 < 0$, they do not. Although inf^* and inf^0 are not observable directly, but $inf^* - inf_0$ is determined by the CT information supply and RHs' cognitive ability. Therefore, we can construct the CT cognition equation (Equation (4)) from Equation (1):

$$y^c = \begin{cases} 1, & inf^* - inf_0 = \alpha^c X^c + \beta^c demon^c + \varepsilon^c > 0 \\ 0, & inf^* - inf_0 = \alpha^c X^c + \beta^c demon^c + \varepsilon^c \leq 0 \end{cases} \tag{4}$$

In the Equation (4), y^c is whether the RH knowns about the CT. If the RH knows this, its value is 1; otherwise, its value is 0; X^c is the factors that related with RHs' cognitive ability; $demon^c$ is the technology demonstration; α^c, β^c are the parameters to be estimated, and ε^c is the error term.

According to the theoretical discussion of stage 2 and Equation (3b), after the RHs have heard about CT ($y^c = 1$), their CT adoption would be determined with $p \cdot g'(A_2)\tilde{e} - (c_1 + c_2\tilde{e}) > 0$. From the previous analysis, we can see that $p \cdot g'(A_2)\tilde{e} - (c_1 + c_2\tilde{e})$ is jointly affected by the real net revenue of CT and RHs' expectation of cost and revenue on production with different technologies; and in the production theory, the former is related to the RHs' inputs on grain production and their personal characteristics, and the latter is related to the technology demonstration in their area. Therefore, we can obtain the CT adoption decision equation (Equation (5)) from Equation (3b):

$$y^a = \begin{cases} 1, & p \cdot g'(A_2)\tilde{e} - (c_1 + c_2\tilde{e}) = \alpha^a X^a + \beta^a demon^a + \varepsilon^a > 0 \\ 0, & p \cdot g'(A_2)\tilde{e} - (c_1 + c_2\tilde{e}) = \alpha^a X^a + \beta^a demon^a + \varepsilon^a \leq 0. \end{cases} \tag{5}$$

In the Equation (5), y^a is whether the RH adopts CT, if the RH has adopted CT, its value is 1, otherwise, its value is 0; X^a is the RHs' production inputs and personal characteristics; $demon^a$ is the technical demonstration in the area where the RH is located, α^a, β^a are the parameters to be estimated, and ε^a is the error term.

According to the discussion in stage 2 and stage 3, after the RH decides to adopt CT ($y^a = 1$), the CT adoption intensity y^p can be expressed as Equation (6):

$$y^p = \alpha^p X^p + \beta^p demon^p + \varepsilon^p \tag{6}$$

In Equation (6), y^p is the RH's CT adoption intensity, which is indicated by the proportion of land area with CT; X^p and $demon^p$ are similar with X^a and $demon^a$ in Equation (5), α^p, β^p are the parameters to be estimated, and ε^p is error term.

The RHs' CT adoption intensity is conditional on having decided to adopt CT that $y^a = 1$, which in turn is conditional upon having heard about CT that $y^c = 1$. Therefore, y^p and X^p, $demon^p$ in Equation (6) can only be observed only if $y^a = 1$ and $y^c = 1$, while y^a and X^a, $demon^a$ in Equation (5) can be observed only if $y^c = 1$, and then the sample self-selection problem must be overcome in the estimation. We assume that the error terms in Equations (4)–(6) are tri-variate normal distribution: $\{\varepsilon^p, \varepsilon^a, \varepsilon^c\} \sim TVN(0, 0, 0, \sigma^2, 1, 1, \Psi^a, \Psi^c, \rho)$, where $\Psi^a = corr(\varepsilon^a, \varepsilon^p)$, $\Psi^c = corr(\varepsilon^c, \varepsilon^p)$ and $\rho = corr(\varepsilon^a, \varepsilon^c)$. Under these assumptions, the conditional probability of adoption that $y^a = 1$ in Equation (5) can be given by

$$\begin{aligned} \text{prob}\left(y^a = 1 | y^c = 1\right) &= \text{E}\left(y^a = 1 inf^* - inf_0 > 0\right) \\ &= \Phi(\alpha^a X^a + \beta^a demon^a) + \rho \frac{\phi(-\alpha^c X^c - \beta^c demon^c)}{1 - \Phi(-\alpha^c X^c - \beta^c demon^c)} \end{aligned} \tag{7}$$

The Equation (7) is a bivariate Probit model with Sample Selection, where $\Phi(.)$ and $\phi(.)$ denote the cumulative distribution function (cdf) and probability density function (pdf) of a univariate normal distribution, $\frac{\phi(-\alpha^c X^c - \beta^c demon^c)}{1 - \Phi(-\alpha^c X^c - \beta^c demon^c)}$ is the inverse Mills ratio that be estimated from Equation (4). It can be seen from Equation (7), $\text{prob}\left(y^a = 1 | y^c = 1\right)$ is an expectation with a truncated normal distribution. If the Probit or Logit regression is directly performed on Equation (5) without considering the premise of $y^c = 1$, the second term on the right side in Equation (7) would be ignored, thus bringing inconsistent estimation for α^a and β^a. Using a maximum likelihood estimation (MLE) on Equation (7),[1] we can obtain the estimation of α^a, β^a, α^c, β^c and $\rho : \hat{\alpha}^a$, $\hat{\beta}^a$, $\hat{\alpha}^c$, $\hat{\beta}^c$ and $\hat{\rho}$. Substituting these estimations into the Equation (6), then it can be extended and written as

$$y^p = \alpha^p X^p + \beta^p demon^p + \hat{\lambda}^c \theta^c + \hat{\lambda}^a \theta^a + \eta \tag{8}$$

In Equation (8), $\hat{\lambda}^c = \phi\left(-\hat{\alpha}^c X^c - \hat{\beta}^c demon^c\right) \cdot \Phi\left[\frac{-\left(\hat{\alpha}^a X^a + \hat{\beta}^a demon^a\right) - \hat{\rho} y^c}{\left(1-\hat{\rho}^2\right)^{\frac{1}{2}}}\right] / \Phi_2$, $\hat{\lambda}^a = \phi\left(-\hat{\alpha}^a X^a - \hat{\beta}^a demon^a\right) \cdot \Phi\left[\frac{-\left(\hat{\alpha}^c X^c + \hat{\beta}^c demon^c\right) - \hat{\rho} y^a}{\left(1-\hat{\rho}^2\right)^{\frac{1}{2}}}\right] / \Phi_2$, and θ^c, θ^a are the parameters to be estimated for $\hat{\lambda}^c$, $\hat{\lambda}^a$, and η is the error term. $\Phi_2(.)$ is a bivariate normal cdf $\Phi(-\hat{\alpha}^c X^c - \hat{\beta}^c demon^c, -\hat{\alpha}^a X^a - \hat{\beta}^a demon^a, \hat{\rho})$. If the sample self-selection problem is not addressed, then $\hat{\lambda}^c \theta^c$ and $\hat{\lambda}^a \theta^a$ in Equation (8) will be ignored and estimations would suffer from omitted variable bias.

3.3. Data and variable description

The RHs data used in this study is from a sample survey of six provinces in two major grain-producing regions of China in 2014, that Heilongjiang Province, Jilin Province and Liaoning Province are in the Northeast China and Hebei Province, Shandong Province and Henan Province are in the Huang-Huai-Hai Plain. In each province, the households are selected with a stratified sampling method, and finally, 845 valid sample households are obtained. In China, the Northeast region and the Huang-Huai-Hai Plain are not only the most important grain producing areas, but also the most important areas for the implementation of CT technology. Therefore, the data used in estimation are well representative.

As discussed above, we use whether RHs known about CT, whether RHs to adopt CT and how much cultivated land with CT as the variable of RHs' CT cognition, CT adoption and CT adoption intensity. CT is a set of systematic planting technologies which aims to protect the productivity and quality of cultivated land by increasing the coverage of straw and green crops, implementing reduced tillage and no-till practices or adopting a diversified rotation and tillage system (Gao, 2007), and the reduced tillage, no-till practices, and subsoiling are the most common practices in China (Gao et al., 2013). Based on this, RHs' CT cognition and adoption refers to their cognition and adoption of reduced tillage, no-tillage, and subsoiling. If RHs hear about at least one of these three practices, we consider they have CT cognition; if one of these three is used in production, we consider they are the CT adoption household; and the adoption intensity is denoted by the proportion of land area using CT.[2]

For the explanatory variables, we use whether has CT demonstration sites in the village (*demon*) and the duration category of demonstration (*dyearg*) to indicate the technical demonstration status that RHs face. If there are technology demonstration sites in the village, the value of *demon* is 1, otherwise it is 0. The duration (*dyearg*) is first calculated with (survey year-setting started year)+1, and then classified into three groups that 0 years (it values 0), 1 to 4 years (it values 1) and greater than or equal to 5 years (it values 2). We use RHs' human capital and social capital to reflect their cognitive ability. The RHs' human capital is indicated by the household head's education years (*edu*). The RHs' social capital is indicated by whether household head has experienced village cadres (*cadre*) and whether the RH is a member of the cooperative (*cooper*); if the household head has experienced village cadres, the value of *cadre* is 1, otherwise it is 0; if the RH is a member of the cooperative, the value of *cooper* is

Table 1. Descriptive statistics of explanatory variables.

	First stage regression			Second stage regression			Third stage regression		
Variable	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.
demon	0.346	0	1	0.532	0	1	0.355	0	1
dyearg	0.421	0	2	0.646	0	2	0.424	0	2
train	0.399	0	1	0.634	0	1	0.494	0	1
age	51.275	23	80	50.064	24	78	49.286	24	78
edu	7.953	0	67	8.153	0	16	8.016	0	16
exp	30.088	2	65	28.781	2	57	28.131	2	57
cadre	0.163	0	1	0.209	0	1	0.184	0	1
cooper	0.217	0	1	0.262	0	1	0.245	0	1
narate	25.588	0	100	24.827	0	100	24.548	0	100
frag	5.278	1	58	5.952	1	58	5.653	1	23
scaleg2	0.346	0	1	0.455	0	1	0.465	0	1
Observations	845			393			248		

Source: A sample survey of six provinces in two major grain-producing regions of China.

Table 2. RHs' cognition and adoption of CT (%).

	Whether heard about CT		Whether to adopt CT		
Province	No	Yes	No	Yes	Adopt intensity
Heilongjiang	11.80	88.20	41.61	58.39	48.69
Jilin	55.63	44.38	78.75	21.25	16.46
Liaoning	50.00	50.00	61.88	38.13	36.51
Hebei	59.84	40.16	71.31	28.69	25.22
Shandong	79.34	20.66	92.56	7.44	7.44
Henan	78.51	21.49	87.60	12.40	8.88
Total	53.49	46.51	70.65	29.35	25.28

Source: A sample survey of six provinces in two major grain-producing regions of China.

1, otherwise it is 0. The proportion of off-farm employment of family labor (*narate*), the total size of cultivated land (*scaleg*) and the degree of fragmentation (*frag*) are used to reflect the RHs' inputs characteristics in grain production. And the *scaleg* is a categorical variable, which divided into two groups by whether the total land size is more than 50 Mu. If the size is less than 50 Mu, its value is 0, and the size is equals to or greater than 50 Mu, its value is 1. Moreover, the age of household head (*age*), whether they have received agricultural technology training (*train*), years of farming (*exp*), and the dummy variables of province (region) are included in the estimation. The descriptive statistics of explanatory variables except for *region* is in Table 1.

4. Empirical results and discussion

4.1. RHs' CT cognition and adoption

Table 2 shows the sample RHs' cognition and adoption of CT. Overall, 46.51% of these RHs reported they have heard about CT, 29.35% of them have adopted CT in their grain production. The crosstab analysis results of CT adoption and cognition show that RHs deciding to adopt CT is entirely pre-determined by whether they heard about it. Among those RHs that heard about CT, 62.34% of them finally have used CT. This confirms that technology cognition is a prerequisite for the occurrence of technology adoption, which to a certain extent verifies the previous theoretical analysis. And in the analysis of CT adoption, ignoring RHs' self-selection behaviors may

Table 3. Technology demonstration and CT adoption: benchmark regression.

	(1) Heckman Two-step		(2) Heckman Probit	
Explanatory variables	Stage 3: Adoption intensity	Stage 2: Adoption decision	Stage 2: Adoption decision	Stage 1: Cognition
demon = 1	−0.399	−0.107	−1.348***	0.967***
	(8.97)	(0.106)	(0.134)	(0.098)
cadre = 1	–	–	–	0.226*
	–	–	–	(0.12)
cooper = 1	–	–	–	0.127
	–	–	–	(0.103)
age	–	–	–	−0.0103**
	–	–	–	(0.00456)
exp	−0.00379	–	–	–
	(0.148)	–	–	–
edu	−0.152	0.0124	−0.00225	−0.00386
	(1.23)	(0.0152)	(0.0257)	(0.0152)
train = 1	−2.541	0.235**	−0.741***	–
	(16.99)	(0.106)	(0.146)	–
narate	−0.134	0.00277	−0.00035	–
	(0.214)	(0.00214)	(0.00244)	–
frag	−1.303	−0.0242	−0.0284*	–
	(1.806)	(0.015)	(0.0156)	–
scaleg2 = 1	−4.959	0.297**	0.0741	0.501***
	(21.54)	(0.124)	(0.155)	(0.0994)
region	Yes	Yes	Yes	No
Constant	Yes	Yes	Yes	Yes
lambda/rho	−43.45	–	−0.9222	–
	(99.8)	–	(0.108)	–
LR test of independence			5.5**	
Wald Chi^2	25.83**		148.53***	
Observations	248	845	393	845

Notes: In the Column 1 of Heckman two-step regression, lambda (Inverse Mills rate) is reported, and in the Column 2 of Heckman Probit regression, the correlation coefficient ρ of the error term is reported.
Source: Author's calculation.

bring serious estimation bias to the results. In terms of adoption intensity, the area of land using CT accounts for 25.28% of the RHs' total cultivated land size. If only statistics with RHs using CT, the area proportion of land using CT would reach 86.07%.

In the provincial statistics, there are obvious inter-provincial and regional differences in RHs' cognition and adoption of CT. And the proportions of sample RHs in the Northeastern China that have CT cognition and adoption are higher than those in the Huang-Huai-Hai Plain. Among these six provinces, RHs in Heilongjiang Province have the most knowledge and use of CT, and RHs in Shandong Province have the least knowledge and use of CT. And these are in line with the fact that the Northeastern region is the main implementation region of the CT program in China.

4.2. The effects of technology demonstration on RHs' CT adoption

4.2.1. Benchmark results

Without considering self-selection in technology cognition, we used Heckman's two-step model as a benchmark regression to investigate the effects of technology demonstration on RHs' CT adoption (Column 1 of Table 3). Meanwhile, considering technology cognition is the pre-requirement of technology adoption, we even use the

Table 4. Technology demonstration and CT adoption: 3SLS estimation.

Variable	Stage 1: cognition	Stage 2: adoption decision	Stage 3: adoption intensity
demon = 1	2.345***	−2.506***	−22.81**
	(0.208)	(0.327)	(8.902)
cadre = 1	0.834***	–	–
	(0.236)	–	–
Cooper	0.632***	–	–
	(0.191)	–	–
Age	−0.0315***	–	–
	(0.00446)	–	–
Edu	−0.026	0.0705	0.205
	(0.0261)	(0.0546)	(0.427)
scaleg2 = 1	1.095***	0.650*	−7.261
	(0.196)	(0.361)	(5.461)
Exp	–	–	−0.0544
	–	–	(0.133)
train = 1	–	−1.925***	10.40**
	–	(0.371)	(4.773)
Narate	–	−0.00353	0.0646
	–	(0.00658)	(0.0586)
Frag	–	−0.0736***	−0.794*
	–	(0.0255)	(0.408)
Region	No	Yes	Yes
imr1	–	–	−131.5***
	–	–	(43.17)
imr2	–	–	−38.17
	–	–	(31.66)
Constant	–	–	Yes
Wald Chi2/F	465.14***		11.50***
Observations	845	393	248

Notes: (1) *** indicates $p < 0.01$, ** indicates $p < 0.05$, *indicates $p < 0.1$; (2) Standard error is in parentheses.
Source: Author's calculation.

Heckman Probit model in this benchmark regression to confirm the existence of self-selection of technology cognition in the CT adoption decision (Column 2 of Table 3).

In Column 1, if without considering the RHs' self-selection of cognition, the technology demonstration is insignificant in the CT adoption. However, after considering this self-selective behavior, the results in Column 2 indicate technical demonstration can significantly promote RHs hearing about CT, but has a significant negative impact on CT adoption. The LR test of the independence between cognition and adoption decision (LR test in Column 2) show that they are significantly related, which means that the RHs' CT adoption is strong pre-determined by the technological cognition and there is serious estimation bias without eliminating the self-selection of cognition. The large coefficients' differences of the same factors in adoption decision in Column 1 and 2 have strongly supported this bias existence.

4.2.2. 3SLS estimation results

For eliminating the self-selection bias from RHs' technical cognition, we re-estimated the effects of technology demonstration with a 3SLS model and the results are shown in Table 4.

4.2.2.1. Technical demonstration and RHs' CT adoption. The results in Table 4 show that technology demonstration has obvious heterogeneous influences on the three stages of RHs' CT adoption. Specifically, technology demonstration has a significant positive effect on RHs' technology cognition, while it is negative in the CT adoption decision and adoption intensity.

The empirical results show that technology demonstration can indeed effectively promote the information diffusion of new technologies in agricultural production, and help producers understand and recognize these new technologies. As a mechanism for diffusing agricultural technology information, technology demonstration is very effective in increasing information supply. However, CT, as an agricultural technology aimed at improving land quality and protecting ecological environment, has the following characteristics compared with traditional tillage: firstly, special no-till fertilizer seeders must be used; secondly, straw residues seriously affect the quality of seeding and require additional crushing and spreading treatment; thirdly, it leads to an increase in weed and insect pests; and fourthly, deep pine operation is required to increase (Kumara et al., 2020). From its technical characteristics, CT not only cannot effectively improve the output and product price of the land cultivated with this technology and may even lead to a decline in output, but also increase the RHs' machinery input and later field management workload and cost (Teklewold et al., 2013). Therefore, the comparative net benefit of CT is lower than that of conventional tillage at present. Especially in the short term, it will be very obvious. This has been confirmed in existing studies. It was found that the main benefit of CT is the protection of soil fertility and quality (Yang et al., 2022). While it facilitates higher land output in the distant future (Holland, 2004; Si et al., 2021), it has little impact on the increase in output in the current period (Zhang et al., 2015), and even results in lower net returns (Corbeels et al., 2014). Therefore, the more information of the CT, RHs could understand the cost and revenue advantages and disadvantages of CT clearly. And under the reality that RHs in China get continuously involved in non-agricultural sectors, they have less likely to adopt CT by the goal of maximizing household income.

4.2.2.2. Other significant factors. In the cognition stage, the RHs that their head is a CPC, they are the member of the cooperative and they operate large scale of cultivated land have a high-level understanding of CT, and the RHs that their head is elder have more less cognition. Among those RHs hearing about CT, the RHs who have participated in the agricultural technology training and have high level of land fragmentation are relatively less likely to adopt CT, and the RHs with larger land size are more likely to adopt CT. Once the RHs have applied CT in their grain production, agricultural technology training is helpful RHs to enlarge land area of CT, while land fragmentation is unhelpful.

Among these significant factors, the negative effect of land fragmentation on CT adoption decision and adoption intensity deserves more attentions. In general, CT is an agricultural technology that requires greater use of machinery and requires higher mechanical operations. At present, the high degree of land fragmentation in rural China is not suitable for the requirements of mechanical operation of CT and the realization of large-scale operation of machinery, and thus the unit production cost cannot be reduced due to the difficulty of achieving economies of scale. Combining the results that RHs with large scale of land size have more adoption of CT, we

Table 5. Demonstration duration and CT adoption.

Variable	Stage 1	Stage 2	Stage 3
dyearg = 1	2.408***	−1.700***	−10.68
	(0.214)	(0.183)	(9.648)
dyearg = 2	2.161***	−2.186***	−12.4
	(0.294)	(0.262)	(11.3)
control	Yes	Yes	Yes
imr1	–	–	Yes
imr2	–	–	Yes
Constant	–	–	Yes
Wald Chi^2/F	511.39***		10.28***
Observations	845	393	248

Notes: (1) *** indicates $p < 0.01$, ** indicates $p < 0.05$, *indicates $p < 0.1$; (2) Standard error is in parentheses.
Source: Author's calculation.

consider that large-scale centralized management of land may be an important prerequisite for the accelerated application of CT in China.

4.2.3. Further discussion based on demonstration duration and land scale

With the continuous demonstration of technology, the long-term benefits of CT that increasing output and improving product quality by land quality improvement will come out. The RHs who have long-term CT demonstration sites around them may learn about these long-term effects, then change their cost-revenue perception of CT and turn to adopt CT. Based on this consideration, we divide the technical demonstration sites into two subgroups of 1–4 years site and ≥5 years site according to their setting duration, and further investigate the effects of demonstration duration on CT adoption. The 3SLS estimation results in Table 5 show that increasing technology demonstration time could not change the relationship of technology demonstration and CT adoption. Whatever in the 1–4 years group or in the ≥5 years group, technology demonstrations can significantly enhance RHs' cognition, reduce the adoption probability, and have no effect on the adoption intensity. In this regard, we consider that the long-term economic benefits of CT are inconspicuous. If the ecological benefits of CT cannot be valuation at all, it will be very difficult for RHs to change their decision-making on CT adoption. The plight of the slowly promotion and application of CT in China will continue for a long time. And how to value the ecological benefits of CT should be an important issue in the CT promotion policy improvement.

Due to the verified dependence of family income on farming, the grain production decisions of large-scale farmers and small-scale farmers have sharp target differentiation. And this may make these two types of RHs have completely different cognitions and behaviors of CT. Some empirical evidences have supported that technology demonstrations have a significant positive effect on promoting the CT adoption of large-scale farmers (Wang et al., 2017), which is completely contrary to the empirical results of this study. Considering that the scale of cultivated land operation may affect the effect of technology demonstration on CT adoption decision, we divided RHs into two subgroups of land area < 50 Mu and ≥ 50 Mu, and re-estimated 3SLS model respectively. The results in Table 6 revealed that technology demonstrations have the similar impacts in all three stages of the decision-making of CT adoption in the large-scale and small-scale farmers group. Regardless of whether technical demonstrations or the demonstration duration is the

Table 6. Technology demonstration and CT adoption: comparison with land scale.

RHs type	Small-scale farmers			Large-scale farmers		
Variable	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3
domen = 1	1.099***	−1.819***	13.01	2.908***	−1.669***	15.78
	(0.223)	(0.456)	(11.29)	(0.339)	(0.393)	(17.11)
control	Yes	Yes	Yes	Yes	Yes	Yes
imr1	–	–	Yes	–	–	Yes
imr2	–	–	Yes	–	–	Yes
Constant	–	–	Yes	–	–	Yes
Wald Chi^2/F	162.62***		6.47***	110.10***		5.04***
dyearg = 1	1.215***	−2.048***	14.05	2.635***	−2.603***	16.23
	(0.28)	(0.443)	(11.39)	(0.38)	(0.629)	(17.15)
dyearg = 2	0.957***	−1.501**	9.056	2.693***	−3.452***	10.79
	(0.305)	(0.652)	(12.65)	(0.519)	(0.719)	(19.06)
control	Yes	Yes	Yes	Yes	Yes	Yes
imr1	–	–	Yes	–	–	Yes
imr2	–	–	Yes	–	–	Yes
Constant	–	–	Yes	–	–	Yes
Wald Chi^2/F	183.25***		6.47***	97.28***		4.71***
Observations	553	214	131	292	179	114

Notes: (1) *** indicates $p < 0.01$, ** indicates $p < 0.05$, *indicates $p < 0.1$; (2) Standard error is in parentheses.
Source: Author's calculation.

variable, the sign and significance of the estimated coefficient of technical demonstration are the same in these two subgroups.

5. Conclusions

The promotion and application of CT is an important part of the realization of China's strategy of 'storing grain in the land'. RHs as the main users of new technology, their adoption are directly related to CT's promotion and application in China. Technology demonstration as an important means to promote the application of CT, its effects on the Chinese RHs' CT adoption are worthy of further discussion. With a sample survey data in the main grain-producing regions, we constructed a theoretical framework of CT adoption decision under output uncertainty and applied a 3S-TAM to explore the effects of technology demonstration on RHs' CT adoption decision.

The results show that: first, CT adoption decision is determined solely by the RHs' perception of CT; second, technology demonstration as an agricultural technology information diffusion mechanism has a significant positive effect on RHs' CT cognition, but the relatively lower economic benefits of CT make it rather a significant negative effect on the occurrence and intensity of adoption; third, although the increasing of technology demonstration time is helpful for RHs to understand the long-term benefits of CT, but because the net revenue of CT are lower and the ecological benefits cannot be valued, it cannot fundamentally convert the RHs' decision from non-adoption to adoption; fourth, technology demonstration has similar effects on CT cognition and adoption of small-scale and large-scale farmers; fifth, the expansion of land scale helps the adoption of CT, but land fragmentation that against mechanical operation requirements of CT would hindered it.

Based on these findings, we consider that to promote the application of CT in China, especially in the main grain-producing areas, the first task is to carry out institutional innovation that incorporating CT into the scope of ecological compensation and accelerating the valuation of the CT's ecological benefits. As a sustainable agricultural technology that emphasizes ecological goals, CT has a strong positive externality. Compared with traditional tillage, its low direct economic benefits are an important reason why RHs' unwillingness to adopt it in production. Institutional arrangements need to be adjusted to promote the conversion of CT's ecological benefits into economic benefits, and then built the internal behavioral incentive for RHs to adopt CT. Therefore, this study believes that to promote the RHs' CT adoption, it is necessary to carry out ecological compensation pilots to change RHs' benefits expectations of CT as well as using technology demonstrations to promote RHs to well understand the CT's operations. In the policy practices, ecological compensation could be started with large-scale farmers in the main grain-producing areas, and then be gradually extended to ordinary farmers and other regions of the country. The second is to increase the investment subsidies for high-standard farmland construction and to promote the land concentration and reduce land fragmentation by encouraging inter-household negotiation and replacement of land, while encouraging the concentration of land to the large-scale farmers. And these measures would create a favorable environment for CT extension in China.

At the same time, we also noticed that the behavioral decision scenarios and constraints behind CT adoption are changing with the increase in agricultural mechanization, level of socialized agricultural services, specialization of agricultural production, awareness of organic production among farmers, and public concern for food health. Therefore, in future studies, further attention can be paid to the role of factors such as mechanization, increased socialization service capacity, and production specialization in CT adoption decisions, and their relations with the effects of technology demonstration on CT adoption.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. We firstly obtained the parameter values α^a, β^a, α^c, β^c by estimation Equations (4) and (5) separately, and then use them as starting values in the MLE of Equation (7).
2. In the calculating of land area with CT, we only calculated one time for those land that using more than one CT practices.

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