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Simultaneous Decisions to Undertake Off-Farm Work and Straw Return: The Role of Cognitive Ability

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Abstract: Using a sample of 1166 maize-planting farmers from Liaoning province in China, in this paper, we provide a new explanation for the slow-proliferation situation of straw return. Both our theoretical and empirical results indicate that the low rate of adoption of straw return can be partly attributed to the farmers' choice to undertake off-farm work. Probit, PSM, IV-probit, and bivariate probit models are utilized to estimate the interdependent nature of these two simultaneous decisions, with an identified causal effect ranging from −0.115 to −0.287. Instead of the "income-increasing effect", our research supports the dominant existence of the "lost-labor effect". Furthermore, intelligent and risk-tolerant farmers undertaking off-farm work are found to have additional negative impacts on the likelihood of straw return adoption. With regard to the mediating mechanisms, we find that the choice of off-farm work may decrease the probability of raising cattle and also downscale arable land, thereby reducing the likelihood of straw return adoption. In line with our proposed model, fluid cognitive ability contributes to the farmers' adoption of straw return by increasing their learning and updating efficiency. In contrast, crystal cognitive ability deters the undertaking of nonfarm work by establishing a comparative advantage in agricultural production, thus indirectly promoting the proliferation of straw incorporation. According to our theoretical and empirical findings, the proper policy interventions proposed mainly include three points. First, governments should endeavor to increase agricultural specialization by further promoting arable land transfer and human capital accumulation in farming. Second, it is beneficial to facilitate the process of learning by doing and social learning by enhancing the human capital levels of farmers. Last, it is necessary to cultivate farmers' inclination towards long-term investment by explaining the concrete benefits of straw return to farmers on a timely basis.

Keywords: off-farm work; straw return; PSM; IV-probit model; bivariate probit model

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1. Introduction

China has witnessed a fast and steady increase in agricultural production during recent decades. Accompanied by the growth in crop yield, straw resources annually produced by China have exceeded 700 million tons since 2014 [1]. Meanwhile, with the improving living standards of farmers, direct demand for straw for cooking and feeding livestock has reduced dramatically [2]. To enhance the demand for crop residuals, using straw as a base material along with biofuel and industry raw materials has been proposed by specialists. However, due to the high costs associated with stalk collection, transportation, and industrial treatment, open burning of straw is still common in some rural areas in China [3], causing significant damage to arable land, including soil erosion [4], soil infertility [5], and a decrease in farmland biodiversity [6]. Bearing this in mind, the 14th Five-Year Plan for Circular Economy Development issued by the State Council of China proposed that the overall utilization rate of crop straw should reach 86% by the year 2025 [7]. Among the five common treatment approaches for utilizing stalks, incorporating mechanically minced straw pieces into the field as manure is considered the most beneficial way of increasing crop yields and promoting arable land protection [8]. Therefore, an increase in the straw return rate has always been the target of relevant policies in recent years, and the recommendations of these policies range from the provision of direct subsidies for adopters of straw return to strict punishment for burning straw in open fields [9].

Compared with the quick diffusion in most developed countries such as the United States of America, Canada, and Japan, where about 70% of crop straw is directly returned to the soil [10], less than 50% of farming land in China adopted straw return in 2019 [11]. Furthermore, there are still great regional variations across China, where the straw return rate of the northeast region is relatively low due to huge straw resources and climate conditions [12]. In contrast to other regions that practice the wheat–maize double cropping system, the majority of farmers in the northeast region prefer to adopt maize mono-cropping due to lower temperature conditions. Our survey conducted in Liaoning province, which is situated in the northeast region, revealed that only 26.2% of the maize straw produced was utilized in the fields, indicating a suboptimal level of incorporation. As relevant research indicates, at least 70.4% of maize straw should be returned to the field to counterbalance the carbon produced in maize cultivation and to achieve the goals of soil protection and crop yield enhancement [13]. The subsidy for farm land with straw coverage of more than 60% was raised to CNY 90 per mu in 2023 by the Liaoning provincial government [14]. Surprisingly, the rising degree of policy stimulus and the lagging dissemination of straw return in Liaoning province have attracted little attention from researchers.

As a method for protective tillage or green agriculture production, straw incorporation benefits farmers in the long term. Furthermore, it is commonly believed that straw return can benefit arable land in several ways, such as by restoring land activity, reducing soil erosion, enhancing soil fertility, and enhancing field ecosystems. Nonetheless, due to combined factors such as the increased uncertainty regarding crop yield and externalities concerning the public environment, the adoption of straw return by farmers is a relatively long process in developing countries such as China. Thus, it is a clear aim for Chinese researchers to identify critical impeding factors to smoothen the transformation process. Based on new-classical economics, early research focused on the analytical framework of profit maximization, aiming to discern the effect of the scale of arable land, individual- and household-level factors, and relevant policies on the probability of straw return adoption [15,16]. The latest exploration has shifted to institutional and behavioral economics; hence, new human capital and bounded rational theory are utilized to explain farmers' conduct with respect to technology adoption [17]. The empirical results of frontier research reveal that the ability to obtain and process information [18], risk and time preference [19], and formal and informal institutional arrangements [20] are factors that have pronounced effects on the decision of a farmer to adopt straw incorporation.

While existing research has yielded fruitful results, there are still two aspects that require further exploration. The first aspect is that incomes from both farm and nonfarm activities determine the wellbeing of rural households [21]. This means that the adoption of new agricultural technologies may be closely related to the decision to undertake nonfarm employment. On the one hand, increased income can speed up the process of adopting modern technology by alleviating the financial constraints of rural households [22]. On the other hand, if time must be allocated between agricultural and non-agricultural activities, the process of adopting innovative technology may be prolonged [23]. The second aspect lies in the lack of exploration of the process of obtaining, updating, and analyzing relevant information about new agricultural technologies. To be specific, we should learn more about the interactive role of off-farm work and cognitive ability in deciding the maximization of total profits from farm production and employment. Theoretically speaking, cognitive ability not only has the power to explain the adoption of straw return to the field but is also an important factor in determining the income from nonfarm activities.

Based on the current state of straw return in China and the existing body of research, we investigated the joint decision between off-farm work and straw return among 1166 maize-planting farmers in Liaoning province. Additionally, we examined the specific influence of cognitive ability on these joint decisions. Our paper contributes to the existing literature in the following three aspects: first, in contrast to previous research neglecting the nature of joint decisions concerning straw return, we provide a convincing theory and empirical evidence that the choice of nonfarm employment significantly decreases the probability of adopting this technology. Second, we comprehensively examine the underlying influences of off-farm work on straw return by proposing the "lost labor effect" and "income-increasing effect". Our analysis of the mediating effect contributes to identifying the channels of off-farm work in respect of the straw-to-field process. Lastly, in addition to the choice of straw return, the determination of undertaking off-farm activities is explored. Concrete roles of human capital, such as cognitive ability and education, are examined to better understand the relationship between off-farm work and straw return. To our knowledge, this study is the first to measure fluid and crystal cognitive ability in the related research field of straw return.

The remaining content is organized as follows: the next section introduces relevant literature concerning straw return and off-farm work. In Section 3, we probe into the theoretical background and propose a hypothesis. Section 4 includes a description of the data and summary statistics. An empirical analysis is conducted in Section 5. We discuss our new findings, research limitations, and policy implications in Section 6. Finally, we present our conclusions in Section 7.

2. Literature Review

2.1. Straw Return Decision

From the angle of disciplines, most of the research on straw-returning determination is presented from the perspective of psychological and management studies. These studies use models such as the theory of planned behavior (TPB) [24], protection motivation theory (PMT) [25], and the unified theory of acceptance and use of technology (UTAUT) [26] to explore the willingness to adopt straw returning. Psychological and social variables such as perceived usefulness, perceived ease, perception of risks, subjective norms, and social trust are considered core determinants of the intention of farmers to utilize straw incorporation [27]. By revealing the psychological process of accepting an innovative technology, this approach has both merits and demerits. The core strength of this approach is the high explaining power of intention to adopt new technology by providing a systematic framework between the psychological constructs [28]. However, one of the drawbacks lies in the possibility that intention may not lead to action under certain circumstances. For example, some studies contend that there are huge discrepancies between willingness and behavior to adopt modern technology [29]. Another shortcoming is that rather than predetermined variables, psychological constructs such as the perceived usefulness of technology are in essence dependent variables, since it is more valuable to focus on how farmers formulate their perception of the usefulness of a new technology.

Instead of focusing on intention or willingness, economists pay more attention to farmers' behavior when adopting a new agricultural technology. In general, farmers are assumed to pursue maximization of profit or wellbeing, although the latest studies have begun to introduce frontier achievements in behavioral economics and new human capital theory. Furthermore, to explain the delayed dissemination of the modern approach to agricultural production, advancements in psychology such as the measurement of time and risk preference are also utilized. There are two major breakthroughs in the latest literature in economics.

The first breakthrough is to consider technology adoption as a dynamic and complex learning process, thus emphasizing the capacity of farmers in information acquisition and processing [30]. From this perspective, one central element entering the decision-making process is that farmers have bounded rationality, so "irrational" conduct such as postponing the adoption of a seemingly beneficial technology is in essence reasonable. During the learning process, farmers are literally Bayesian learners, continuously updating the information about the uncertainty of utilizing new technology [31]. Among the information-gathering channels, “learning by doing” and social learning are equally important in disseminating technology knowledge [32]. The differences between these two channels are that the efficiency of “learning by doing” is positively related to cognitive abilities, while farmers with low levels of cognitive ability are more likely to rely on social learning [33]. Empirical evidence indicates that if the adoption of technology is in combination with other factors such as different tillage, fertilization, and irrigation practices, the resulting uncertainty and complexity will entail a more influential role for cognitive ability [34]. The complexity of technology also highlights the salience of social learning, which not only means learning from others but also signifies learning together with others [35]. In addition to the evidence that the cumulative experiences of all the farmers in a village can positively lead to the diffusion of a technology [36], both the “threshold model” and network theory are proposed to signify the importance of tight social relationships in alleviating the constraints of information friction [37].

The second major breakthrough involves recognizing personal characteristics such as risk and time preference as factors that influence the spread of technology in underdeveloped countries. Recent research suggests that when adopting a new technology introduces uncertainty, the process of adoption may be delayed because farmers are more likely to avoid ambiguity [38]. This means that without proper intervention, the delayed diffusion process of technology adoption can be long-lasting [39]. Another interesting finding is that farmers do not simply conform to mean-variance analysis but pay more attention to the lower tail of the payoff distribution [40]. Concluding from the downside risk-averse feature of developing counties, the low adoption rate of straw return can be partly explained since, if it is not properly handled, straw return may lead to the downside risk of decreased crop yields caused by pests and disease. In addition to risk preference, time preference plays a significant role in explaining procrastination in relation to new technology in poor regions [41]. One viewpoint is that future-biased farmers may save up and thus be more likely to migrate to cities, with present-biased farmers remaining in rural regions [42]. Therefore, the problem lies in the fact that even if farmers make clear the payoff distribution of introducing a new technology, high subjective discounting rates can decrease the present value of a future investment [43]. In a survey of rural regions in Uganda, Bauer and Chytilová attributed the present-oriented feature of farmers to low education levels [44]. The negative impact of time preference on the straw return behavior of Chinese farmers was also identified by Mao et al., further demonstrating the importance of enough patience in evaluating the tradeoffs between intertemporal choices [45].

2.2. Off-Farm Work and Agricultural Investment

As China’s economy is in transition, it has been relaxing its household registration system during the past forty years, generating a large number of rural migrant workers previously restricted to the countryside. According to official statistics, there will be about 285 million rural migrant workers in 2020 [46]. However, most of them were confined to nonstandard employment, pursuing contingent, precarious, and flexible jobs with few social security benefits [47]. Therefore, for most rural migrant workers, their household members still undertake farming production to maximize the total earnings of the family. Off-farm work provides important sources of monetary compensation in all developing countries where income from farming is more limited [48]. From the perspective of agricultural development, economists have conducted intensive research concerning the effect of off-farm activities on the proliferation of agricultural technology [49]. The conclusions diverge into two contradictory strands.

The first viewpoint is that off-farm work is complementary to the modernization of agriculture. This strand of literature contends that participation in nonfarm activities can alleviate poverty, thus contributing to relaxing the financial constraints hindering the adoption of new technology [50]. This viewpoint is consistent with the prediction that farmers, compared with urban inhabitants, are more susceptible to credit constraints because insurance and credit markets in rural regions are not well developed, especially in developing countries [51]. Separately setting income from off-farm work and expenditure on farming as the independent and dependent variables, the elasticity estimated by Kilic et al. is larger than 0.1, which means that more than 10 percent of nonfarm income is spent on agricultural production [52]. Another channel proposed by Oseni and Winters is the risk diversification mechanism in respect of maintaining a steady income stream, for profits gained from farming are vulnerable to natural disasters [53]. Khanal and Mishra confirmed that the income smoothing function for off-farm work can reduce the variability of yearly payoffs, which is also beneficial for long-term agricultural investment [54].

The second viewpoint is that off-farm work can substitute for the activities carried out in farming, consequently stifling the innovation of agricultural production. Although some studies admit that off-farm income-generating activities improve the overall wellbeing of rural households, some studies have revealed a negative effect on farm investment in technology [55]. This channel is called the lost labor effect, which stresses that if a member of a household is engaging in non-agricultural activities, time or other resources must be sacrificed [56]. Based on a sample from Jiangxi province in China, Feng et al. confirmed the lost labor effect by finding that soil-improving investments such as the use of green manure are significantly reduced by the decision to undertake nonfarm work [57]. Another study on rural regions in China also identified the pronounced negative effect of nonfarm work on the use of fertilizer and manure [58].

3. Theoretical Analysis

The choice of a straw-returning process can be split into two stages. In the first stage, farmers with bounded rationality will consider time allocations between nonfarm and farming activities based on their human capital levels. If higher levels of education and cognitive ability lead to a higher probability of nonfarm participation, then time spent on farming will diminish but labor earnings will rise, which can alleviate the financial constraints impeding the adoption of new agricultural technologies. In the second stage, based on the given time resources allocated to farming and the income level obtained from off-farm jobs, cognitive abilities determine efficiency through processing and updating the gathered information about the new technology. The other dimension of cognitive ability is the accumulated knowledge about maize planting, which contributes to a better understanding of the payoffs resulting from straw returning.

Relying on the above analysis, we developed a joint determination model of nonfarm employment and straw return based on the farm household model first proposed by Huffman and then revised by Goodwin B K and Mishra [59,60].

First, suppose a rural family consists of a household head and their spouse; the utility level U is determined by leisure L_l, and the consumption of goods and services is C.

The utility of the family can be modeled as follows:

$$U = U(L_l,\ C) \tag{1}$$

The maximization of utility is subject to the following three constraints. Then, income constraints are set as follows:

$$P_g G + W_f X_f = P_q Q + W_m L_m + A \tag{2}$$

where P_g and G stand for the price and amount of goods obtained in the market, respectively. X_f and W_f are the inputs of the farm and the price of adopting straw return from the market. $P_q Q$ denotes the income from farming, while $W_m L_m$ and A represent income from the labor market and assets initially possessed, respectively.

Time constraints are set as follows:

$$T = F(\Gamma) + L_m + L_l \tag{3}$$

Equation (3) signifies that the total time resources of this representative family are allocated among farming $F(\Gamma)$, off-farm work L_m, and leisure L_l.

The production function of farming can be set as follows:

$$Q = Q\Big[X_f(\Gamma), F(\Gamma), H, \Gamma, \mathrm{R}\Big] \tag{4}$$

Equation (4) supposes that the farming output depends on the input purchased from the market X_f, the total labor of husband and wife $F(\Gamma)$, the human capital level of household H, and the adoption intensity of technology Γ. In addition, suppose that there are two levels of Γ, i.e., Γ_0 and Γ_1, representing the adoption of straw returning or not, respectively. Let both the inputs of the farm and the time allocation depend on the adoption of straw return. Further, human capital H includes cognitive ability, education, and health.

For the above four equations, we further assume that the prices of input factors, commodities, and the wage rate of nonfarm work are all exogenously determined. Under this assumption, the first-order condition can be found using the Lagrange expression:

$$L = U(L_l,\ C) + \lambda \left\{P_q\ Q\Big[X_f(\Gamma), F(\Gamma), H, \Gamma, \mathrm{R}\Big] - W_f X_f(\Gamma) + W_m L_m + A\right\} + \mu(T - F(\Gamma) + L_m + L_l) \tag{5}$$

Then, the off-farm participation can be found from the following three equations conforming to the Kuhn–Tucker conditions:

$$\partial L/\partial \mathrm{F} = \lambda P_q\ (\partial Q/\partial \mathrm{F}) - \mu \tag{6}$$

$$\partial L/\partial \mathrm{L}_m = \lambda W - \mu \leq 0 \tag{7}$$

$$\partial L/\partial \mathrm{L}_l = U_{L_m} - \mu = 0 \tag{8}$$

Under the corner solution specified by the following equation, this representative family chooses to participate in off-farm work.

$$W > \mu/\lambda = P_q\ (\partial Q/\partial \mathrm{F}) \tag{9}$$

To be specific, Equation (9) means that participation in off-farm work depends on whether the marginal benefits of market employment (wage rate from employment) are larger than the marginal benefits from agricultural production. Of the human capital variables, education plays a vital role in signaling productivity, therefore contributing to the likelihood of choosing off-farm work.

The total derivative of $\mathrm{d}q/\mathrm{d}\Gamma$ can be expressed as follows:

$$\frac{\partial L}{\partial \Gamma} = \lambda \left\{ P_q \left[\left(\frac{\partial Q}{\partial \mathrm{X}}\right)\left(\frac{\mathrm{dX}}{\mathrm{d}\Gamma}\right) + \left(\frac{\partial Q}{\partial \mathrm{X}}\right)\left(\frac{\mathrm{dX}}{\mathrm{d}\Gamma}\right) + \frac{\partial Q}{\mathrm{d}\Gamma}\right] - W\frac{\mathrm{dX}}{\mathrm{d}\Gamma}\right\} - \mu\frac{\mathrm{dF}}{\mathrm{d}\Gamma} \leq 0 \tag{10}$$

From Equations (9) and (10), we can obtain the following:

$$P_q\frac{\partial Q}{\mathrm{d}\Gamma} - W\frac{\mathrm{dX}}{\mathrm{d}\Gamma} - P_g\big(U_L/U_g\big)\ \frac{\mathrm{dF}}{\mathrm{d}\Gamma} \leq 0 \tag{11}$$

The indication of Equation (11) is that if the marginal benefit of adopting straw returning is larger than the sum of the monetary marginal cost of farming inputs and the time marginal cost of the farming work, then adoption of this new production method is more profitable. Otherwise, farmers will not adopt straw returns. Based on the previous literature, fluid and crystal cognitive abilities both increase the marginal benefits of adopting straw return.

The above equations signify that the choice to undertake off-farm work may impact the adoption of straw return in two channels. The first channel is that off-farm work may increase the likelihood of straw return by raising the income level, which reduces the marginal cost of farming inputs. The second channel is via the "lost labor effect", which reduces the probability of adopting straw return, since off-farm work can crowd out the time needed to adopt straw return. Therefore, it is necessary to empirically test which of the channels dominates.

4. Methodology and Data

4.1. Methodology

4.1.1. Propensity Score Matching (PSM)

This method is used to estimate the treatment effect of undertaking nonfarm work on the probability of adopting straw incorporation. The notion of the propensity score was first proposed by Rosenbaum and Rubin [61] to denote the probability of an individual being treated given his observed covariates:

$$P = (D = 1 \mid X) = P(X) \tag{12}$$

Under the assumptions of unconfoundedness, the probability of being treated is totally determined by covariates but not by unobservable confounding factors. Moreover, if there is a large enough overlap region of common support, we can obtain a sample to derive the mean gap of two balanced groups with similar propensity scores. After reducing the estimation bias caused by unbalanced covariates [62], the average treated effect for the treated group (ATT) of undertaking nonfarm work on the probability of adopting straw incorporation can be expressed as follows:

$$\tau_{ATT}^{PSM} = E_{P(X)|D=1}\{E[Y(1)|\ D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\} \tag{13}$$

4.1.2. Instrumental Variable Probit Regression (IV-Probit)

The endogeneity of undertaking nonfarm work on the adoption of straw return is generated by the feature of these two simultaneous joint decisions. Therefore, if the probit model is used, a biased coefficient will be obtained. In addition to the PSM method, another method by which to identify the causal effect of an endogenous variable on the binary dependent variable is to select a valid instrument satisfying the exclusion rule [63]. To be specific, the instrument variable does not impact the probability of adopting straw return but works through the channel of influencing the choice of nonfarm work.

The IV-probit model includes two regressed equations [64]. Firstly, the choice of choosing nonfarm work is regressed on the instrumental variable and the other independent variables.

$$P(O_i = 1) = \alpha X_i + \gamma Z + \rho_i \tag{14}$$

Secondly, the probability of adopting straw return is regressed on the predicted value of $P(O_i = 1)$ using a probit model.

$$P(R_i = 1) = \beta X_i + \delta \hat{O} + \sigma_i \tag{15}$$

Due to the exogenous nature of $\hat{O}$, the unbiased coefficient δ of $\hat{O}$ on $P(R_i = 1)$ can be estimated.

4.1.3. Bivariate Probit Model

This method can be used to explore the joint decision between off-farm work and straw returning. If they are negatively related, the negative effect of off-farm work on straw return can also be identified. These two decisions can be specified by Equations (9) and (11), respectively; we can therefore obtain the specific equations of joint decisions.

First, let O_i^* be a latent variable denoting the gap between the wage rate for off farm work and the marginal substitution rate between leisure and consumption. Although O_i^* is subjective and thus unobserved, we can observe the choice to undertake off-farm work O_i. The relation between O_i^* and O_i can be expressed by the following equation:

$$O_i^* = \alpha X_i + \varepsilon_i, \text{ where } O_i = \begin{cases} 1 & if\ O_i^* > 0 \\ 0 & otherwize \end{cases} \tag{16}$$

Second, let R_i^* be a latent variable representing the difference between the marginal benefit of adopting straw return and its marginal cost. R_i^* is also unobservable. Nonetheless, we can observe the actual choice of rural households in adopting this technology R_i. Their relationship can also be modeled as follows:

$$R_i^* = \beta X_i + \sigma_i, \text{ where } R_i = \begin{cases} 1 & if\ R_i^* > 0 \\ 0 & otherwize \end{cases} \tag{17}$$

The error term of Equations (16) and (17) can be denoted as follows:

$$\begin{pmatrix} \varepsilon_i \\ \sigma_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & \rho_{\sigma\varepsilon} \\ \rho_{\varepsilon\sigma} & 1 \end{bmatrix} \right) \tag{18}$$

where $\rho_{\sigma\varepsilon}$ signifies the correlation coefficient between the error terms of Equations (16) and (17). If the value of $\rho_{\sigma\varepsilon}$ estimated using the bivariate probit method is significant, then we can conclude that these two decisions are related or interdependent.

4.2. Data and Variables

Among the three provinces situated in the northeastern region of China, Liaoning province boasts the largest population, with approximately 42 million individuals, of whom around 27% reside in rural areas. The data we gathered was derived from a cross-sectional household survey conducted between June and August of 2022, specifically targeting rural households engaged in maize cultivation in Liaoning province. To guarantee the random sampling rule, we first selected 11 regions of the 14 prefecture cities of this province according to the regional distribution of population, arable land per capita, and economic development level. The selected regions were Shenyang, Dalian, Fushun, Liaoyang, Benxi, Fuxin, Anshan, Huludao, Chaoyang, Jinzhou, and Tieling. We then used the approach of stratified sampling by randomly choosing one county for every region, four villages for every county, and 25–32 rural households for every village. We hired 35 investigators and trained them for a week in May. Then, for the following three months, 1333 household heads were interviewed face-to-face to record their answers to various questions at the individual, family, and village levels. After checking the validity, we finally obtained 1166 viable questionnaires.

Our dependent variable and core independent variable were both dichotomous, standing for the binary choices of straw return adoption and off-farm work, respectively. We first controlled the cognitive abilities of the household head, which were split into fluid and crystal cognitive abilities. Referring to the questionnaire of Frederick, fluid cognitive ability was evaluated using six questions on the abilities of reading, information acquisition, reasoning, and numerical analysis [65]. Seven questions concerning knowledge in respect of maize planting were designed to assess the crystal's cognitive ability regarding maize planting. For the thirteen questions, there was only one correct answer for the respondents to choose. Therefore, higher scores meant higher levels of ability. Time preference was measured using a subjective discounting rate by eliciting the equal value of CNY 100 in the next year [66]. We asked the subjects to respond to four binary choices, each with an increasing average maize yield but higher fluctuations, to evaluate their risk preference [67]. In addition to cognitive ability, human capital variables included years of formal education and the self-reported health conditions of the household head. Rather than measuring geographic distance, we used the social capital level as the efficiency of social learning to signify the complex contagion effect on the diffusion of straw return. To be specific, the family head's social capital levels were measured in four dimensions: social network, social trust, social reputation, and social participation [68]. In addition, variables at individual and family levels, such as age, gender, number of family members, family income, raising cattle or not, and arable land per capita, were all surveyed. Finally, the impact of the government, such as through propagation and punishment concerning straw return and burning, was also included.

Detailed descriptions of the variables are reported in Table 1.

Table 1. Descriptions of variables.

Variable Name	Variable Description
Straw return	1 stands for adopting straw return, 0 otherwise
Nonfarm work	1 stands for undertaking off-farm work, 0 otherwise
Fluid ability	Tested scores of fluid cognitive ability (Standardized)
Crystal ability	Tested scores of crystal cognitive ability (Standardized)
Time preference	Subjective discounted rate (%)
Risk preference	Risk aversion of the family head (standardized)
Age	Age of the household
Gender	1 stands for female, 0 for male
Education	Formal education years of the household head
Health	Self-reported health (five grades)
Family income	Total family income in 2021 (in thousand yuan)
Family number	Number of family members
Land per capita	Arable land per capita (mu)
Raising cattle	1 stands for raising cattle, 0 indicated no raising cattle
Social network	Social network of the family head (five grades)
Social trust	Social trust of the family head (five grades)
Social reputation	Social reputation of the family head (five grades)
Social participation	Social participation of the family head (five grades)
Propagation	Propagation of the government on straw return (five grades)
Punishment	Punishment of the government on straw burning (five grades)
Work * fluid	Nonfarm work * fluid cognitive ability
Work * risk	Nonfarm work * risk preference

5. Empirical Analysis

5.1. Summary Statistics

In order to facilitate a more comprehensive empirical analysis, Table 2 provides a systematic description of the variations in variable distribution between two distinct groups (adopters and non-adopters of straw return), as well as farmers engaged in nonfarm work versus those without such an occupation.

Table 2 indicates that only 54.1 percent of the maize farmers have adopted straw return in Liaoning province, and systematic discrepancies exist between nonadopters and adopters of straw return. To be specific, compared with nonadopters, a lower percentage of adopters undertake nonfarm work. Moreover, adopters apparently have higher levels of human capital and social capital, which can manifest as better fluid and crystal cognition, better education, and owning more social resources or recognition. Concerning personal preference, straw return adopters seem to be more future-biased but display little edge in risk tolerance. The statistical figures also show that straw return adopters are on average younger and healthier and possess larger amounts of arable land. Moreover, more than half of the straw return adopters raise cattle, which is much higher than that of nonadopters. Finally, it seems that the degree of propagation on straw return by the government is obviously higher for the adopters.

About 15% of farmers choose to pursue off-farm work, while the other 85% choose to undertake farming full-time. Striking differences can also be found between farmers engaged in nonfarm work and those who are not. One apparent difference is that it seems to be more likely for farmers without nonfarm work to adopt straw return. Nonetheless, the correlation between human capital and undertaking nonfarm work bifurcates. Specifically, although farmers engaged in nonfarm work are on average more intelligent and better educated, they obviously accumulate less knowledge about maize planting. Compared with full-time farmers, farmers undertaking nonfarm work are also younger, healthier, and wealthier, although they possess less arable land. In addition, there are small gaps in personal preference and the levels of social capital between them.

Table 2. Summary statistics.

Variable	Adopting Straw Return or Not		With or without a Nonfarm Job	
	Nonadopters	Adopters	Without an Off-Farm Job	With an Off-Farm Job
	Mean	Mean	Mean	Mean
Nonfarm work	0.19	0.11	0	1
Straw return	0	1	0.56	0.42
Fluid cognitive ability	−0.13	0.11	−0.04	0.21
Crystal cognitive ability	−0.07	0.06	0.04	−0.24
Time preference	9.34	8.90	9.12	9.01
Risk preference	0.77	0.79	0.78	0.78
Age	59.3	55.36	58.17	51.38
Gender	0.45	0.41	0.44	0.36
Education	7.33	7.71	7.37	8.49
Health	4.06	4.41	4.21	4.51
Family income	40.77	58.45	48.74	59.49
Family number	3.6	4	3.75	4.2
Land per capita	6.58	10.73	9.21	6.61
Raising cattle	0.037	0.55	0.33	0.25
Social network	3.36	3.49	3.42	3.45
Social trust	3.78	3.91	3.85	3.88
Social reputation	2.89	3.08	2.98	3.05
Social participation	3.45	3.69	3.6	3.48
Propagation	3.15	3.50	3.30	3.62
Punishment	4.26	4.19	4.21	4.27
Observations	535	631	993	173

In summary, our survey findings indicate that the straw return rate for maize in Liaoning province is lower compared to other regions in China. Additionally, there appears to be a negative correlation between the decision to engage in off-farm work and the adoption of straw return, as farmers involved in nonfarm activities are less inclined to incorporate straw. However, it should be acknowledged that further empirical analysis is necessary to test the causal relationship.

5.2. Empirical Analysis

5.2.1. Stepwise Regression Method

To disclose the effect of undertaking off-farm work on the probability of adopting straw return, we used the stepwise regression method by adding controlled and interaction variables stepwise. In Table 3, we present six probit regressions to show changes in the marginal effects of off-farm work and other controlled variables on the dependent variable.

According to Table 3, it is more likely for farmers with higher intelligence and more planting knowledge to adopt straw return. Nonetheless, inclusion of the “raising cattle or not” variable makes the direct effect of fluid cognitive ability insignificant, which means that more intelligent farmers have a higher probability of raising cattle. Despite the insignificant effect of risk preference, its interaction with a choice of off-farm work can exert pronounced impacts. In addition, it is more likely for healthier household heads, larger families, families with higher incomes, and families with more arable land to adopt a straw return. Concerning the social learning effect, both higher levels of social trust and participation facilitate the adoption of straw returns. In contrast to the significant effect of government propagation, punishment for straw burning in open fields seems to have an insignificant effect on straw return.

Table 3. Empirical results of stepwise regression of the probit model.

	(1)	(2)	(3)	(4)	(5)	(6)
Off-farm work	−0.170 ***	−0.231 ***	−0.223 ***	−0.235 ***	−0.115 ***	0.031
	(−4.23)	(−5.97)	(−5.77)	(−6.13)	(−3.51)	(0.41)
Fluid cognitive ability	0.058 ***	0.035 **	0.030 **	0.028 *	0.014	0.025 *
	(4.00)	(2.44)	(2.09)	(1.94)	(1.20)	(1.94)
Crystal cognitive ability	0.030 **	0.034 **	0.031 **	0.026 *	0.031 ***	0.031 ***
	(2.06)	(2.47)	(2.21)	(1.84)	(2.67)	(2.64)
Time preference	−0.016 *	−0.011	−0.013	−0.011	−0.007	−0.007
	(−1.91)	(−1.43)	(−1.63)	(−1.46)	(−1.07)	(−1.14)
Risk preference	0.022	−0.007	−0.033	−0.034	−0.027	−0.000
	(0.57)	(−0.19)	(−0.88)	(−0.89)	(−0.88)	(−0.01)
Education	0.014 **	−0.002	−0.004	−0.005	−0.001	−0.001
	(2.32)	(−0.28)	(−0.70)	(−0.79)	(−0.20)	(−0.16)
Age		−0.005 ***	−0.005 ***	−0.005 ***	−0.000	−0.000
		(−3.69)	(−3.81)	(−3.91)	(−0.03)	(−0.05)
Gender		−0.057 **	−0.054 *	−0.054 *	−0.019	−0.020
		(−2.02)	(−1.90)	(−1.92)	(−0.83)	(−0.87)
Health		0.079 ***	0.070 ***	0.071 ***	0.051 ***	0.050 ***
		(4.65)	(4.10)	(4.19)	(3.66)	(3.61)
Family income		0.001 ***	0.001 ***	0.001 ***	0.000	0.000
		(2.73)	(2.58)	(2.80)	(0.96)	(0.95)
Family number		0.034 ***	0.033 ***	0.032 ***	0.021 ***	0.021 ***
		(3.68)	(3.59)	(3.46)	(2.72)	(2.70)
Land per capita		0.003 **	0.003 **	0.002 *	0.003 ***	0.003 ***
		(2.10)	(2.05)	(1.69)	(2.79)	(2.80)
Social network			−0.014	−0.007	−0.032	−0.032
			(−0.42)	(−0.21)	(−1.21)	(−1.23)
Social trust			0.037	0.026	0.047	0.052*
			(1.07)	(0.76)	(1.64)	(1.82)
Social reputation			0.018	0.007	0.013	0.009
			(0.82)	(0.31)	(0.77)	(0.50)
Social participation			0.039 **	0.039 **	0.063 ***	0.063 ***
			(2.04)	(2.06)	(3.98)	(4.03)
Propagation				0.045 ***	0.050 ***	0.050 ***
				(4.39)	(5.75)	(5.78)
Punishment				−0.024	−0.026**	−0.026 **
				(−1.57)	(−2.00)	(−1.99)
Raising cattle					0.541***	0.540 ***
					(25.47)	(25.58)
Work * Fluid						−0.062 *
						(−1.94)
Work * Risk						−0.177 **
						(−2.02)
Pseudo R^2	0.0303	0.0944	0.1019	0.1144	0.357	0.3624
Observations	1017	1017	1017	1017	1017	1017

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Marginal effects rather than coefficients are reported.

For the effect of nonfarm activities, undertaking off-farm work significantly decreases the probability of straw return by more than 0.23. However, when the dummy variable "raising cattle or not" is controlled, this effect drops dramatically to 11.5%. More importantly, the interaction term between off-farm work and fluid cognitive ability is pronounced. This indicates that, for farmers with higher levels of fluid cognitive ability, undertaking off-farm work means a lower probability of adopting straw return. Similarly, risk-tolerant farmers have higher tendencies not to adopt straw return if they choose off-farm work. In summary, the empirical results of the stepwise regression support both the direct and interaction effects of off-farm work on the dependent variable. Of the variables, raising cattle or not seems to have a large effect on the pseudo R^2 value and the coefficient of off-farm work.

To further probe into the influencing channel of off-farm work on the dependent variable, the direct and indirect effects of this channel were empirically tested. We sequentially explored the mediating roles of raising cattle, arable land per capita, and health, as Table 4 reports. Of the mediators, raising cattle and land per capita were categorized into the lost labor channel, since undertaking off-farm work will decrease the probability of raising cattle and the scale of arable land due to the limitedness of time. Health acts as a mediator aroused by the income-increasing channel because off-farm work increases the family income and then positively impacts the health condition of farmers.

Table 4. Empirical test of mediating effects.

Channels	Mediator	Effects	Coefficient	Z	$p > Z$
Lost labor channel	Raising cattle	Indirect effect	−0.104 ***	−4.94	0.000
		Direct effect	−0.137 ***	−4.18	0.000
		Total effects	−0.241 ***	−6.01	0.000
	Land per capita	Indirect effect	−0.010 **	−2.12	0.034
		Direct effect	−0.137 ***	−4.01	0.000
		Total effects	−0.147 ***	−4.34	0.000
Income-increasing channel	Health	Indirect effect	0.009 **	2.09	0.036
		Direct effect	−0.137 ***	−4.14	0.000
		Total effects	−0.128 ***	−3.89	0.000

Note: *** and ** denote significance at 1% and 5% levels, respectively.

According to Table 4, the direct effect of undertaking off-farm work on the probability of adopting straw return is −0.137. The indirect effects of off-farm work on straw return via raising cattle and land per capita are, respectively, −0.104 and −0.01, which reveals that the lost labor channel is the main mechanism. To be specific, once employed, farmers have less energy to raise livestock or expand their farming scale. Raising cattle facilitates the adoption of straw return because digested crop straw will be returned to the field as manure. In addition, a larger scale of arable land can contribute to straw return due to the scale economy effect. For the income-increasing channel, rising income facilitates the improvement of health, which is beneficial to the adoption of straw returns. In summary, two channels and three mediators were identified, and the lost labor channel was more salient.

However, systematic discrepancies may exist between farmers undertaking nonfarm work and full-time farmers, as indicated by the results of the summary statistics. We therefore used the PSM and IV-probit methods separately to make these two groups more comparable by controlling or alleviating the self-selection bias.

5.2.2. PSM Method

Cross-sectional data analysis is prone to endogeneity, so we first utilized the PSM method to alleviate this problem. The core idea of the PSM method is to pair the treatment group and the control group together with similar propensity scores if random assignments are not available [69]. First, the logit model was used to calculate the probability of undertaking off-farm work, and the controlled variables included all the determinates in Table 3. Then, we utilized the three most commonly used PSM methods (radius matching, kernel matching, and the stratification method) to reduce the selection bias [70]. As recommended by Becker and Caliendo [71], we set the caliper of the radius match to 0.01. After excluding the unmatched units outside the common support region, most of the samples were kept.

Furthermore, as the table below indicates, bias between the treatment and comparison groups was reduced substantially after the implementation of matching. Especially for the radius- and kernel-matching methods, mean biases decreased to 3% and 2%, respectively. The four matching methods are hence effective in balancing the distribution of the covariates, since the initial mean bias is as high as 20.1%. After pairing the treated and untreated groups, we obtained a counterfactual effect of pursuing off-farm work on the probability of adopting straw return. The treatment effects for the treated group are reported in Table 5.

Table 5. Empirical results of PSM.

Matching Methods	Mean Bias	Treated	Controls	Difference (ATT)	T (Z) Value
Unmatched	20.1	0.416	0.563	−0.147 ***	−3.59
Radius	3.6	0.413	0.528	−0.114 **	−2.42
Kernel	2.5	0.413	0.546	−0.133 **	−2.86
Stratification	3.3	0.413	0.556	−0.144 ***	−3.62

Note: *** and ** denote significance at 1% and 5% levels, respectively.

Table 5 reveals that after controlling for the selection bias, the difference between treatment and comparison groups decreased slightly from −0.147 to more than −0.11. This means that the systematic discrepancies between these two groups cause a downward bias if not well controlled. In other words, PSM methods also indicate that the choice of off-farm work will significantly decrease the likelihood of straw return. In summary, the results of PSM are all greater than −0.100, a little larger than those of stepwise regression, which are about 0.115.

5.2.3. IV-Probit Model

One criticism of PSM is that if the effects of the unobservable variable on the propensity scores cannot be ignored, then the seemingly balanced matching method cannot efficiently decrease the selection bias. Against this background, an instrumental variable probit regression model was also used to control the bias. We argue that party membership in the CPC, road conditions, and the natural disasters of the past five years in this village are all valid instrumental variables [72]. This is because party membership and better road conditions mean more opportunities for off-farm work, but these two variables may not impact the choice of straw return directly. Furthermore, more severe natural disasters will negatively impact the income from farming, thus influencing the choice of off-farm work. As described in Section 4.2, the specification of the IV-probit model is similar to two-stage least-squares regression. The first-stage regression can obtain the predicted value of the treatment variable by regressing the instrumental variable and the other independent variables. Then, an unbiased estimation of the treatment effect can be achieved for the second regressed equation. Compared with PSM, IV-probit does not rely on the assumption of ignorability; thus, the results may be more robust. Table 6 reports the results of both the probit and IV-probit models.

The table above shows that after controlling the predicted value of the probability of undertaking nonfarm work, the t values of some independent variables dropped pronouncedly, although their coefficients remained almost the same. Specifically, the t values of nonfarm work, time preference, income of family, and social participation decreased significantly, partly because the predicted value already contained some of their information. Despite the decreasing significance, the results of the IV-probit model indicate that the marginal effect of nonfarm work on the probability of adopting straw return rises dramatically. Therefore, similar to the results of the PSM method, omitting the endogeneity problem causes a downward bias. In summary, in addition to PSM, the IV-probit model identifies a significant negative effect of nonfarm work on the adoption of straw return, and the estimated coefficient is larger compared with those of the probit and PSM models. Our results indicate that if self-selection bias is better controlled, the marginal effect increases from −0.115 to −0.287.

Table 6. Marginal effects of IV-probit models.

Variable	(1) Probit	(2) IV-Probit First Stage	(3) IV-Probit Second Stage
Nonfarm work	−0.115 ***		−0.287 *
	(−3.51)		(−1.74)
Fluid cognitive ability	0.014	0.009	0.016
	(1.20)	(0.90)	(1.35)
Crystal cognitive ability	0.031 ***	−0.022 **	0.026 **
	(2.67)	(−2.21)	(2.00)
Time preference	−0.007	0.001	−0.007
	(−1.07)	(0.23)	(−1.00)
Risk preference	−0.027	−0.007	−0.028
	(−0.88)	(−0.26)	(−0.90)
Age	−0.001	0.008 *	0.001
	(−0.20)	(1.80)	(0.16)
Gender	−0.000	−0.006 ***	−0.001
	(−0.03)	(−5.77)	(−0.76)
Education	−0.019	−0.047 **	−0.030
	(−0.83)	(−2.36)	(−1.19)
Health	0.051 ***	0.037 ***	0.056 ***
	(3.66)	(2.68)	(3.79)
Family income	0.000	0.000	0.000
	(0.96)	(1.31)	(1.04)
Family number	0.021 ***	0.010	0.024 ***
	(2.72)	(1.56)	(2.98)
Land per capita	0.003 ***	−0.003 ***	0.002 **
	(2.79)	(−2.69)	(2.11)
Social network	−0.032	0.002	−0.031
	(−1.21)	(0.08)	(−1.16)
Social trust	0.047	−0.011	0.048*
	(1.64)	(−0.44)	(1.67)
Social reputation	0.013	0.004	0.013
	(0.77)	(0.28)	(0.77)
Social participation	0.063 ***	−0.043 ***	0.056 ***
	(3.98)	(−3.19)	(3.25)
Propagation	0.050 ***	0.023 ***	0.056 ***
	(5.75)	(3.00)	(5.74)
Punishment	−0.026 **	0.014	−0.026 **
	(−2.00)	(1.29)	(−2.01)
Raising cattle	0.541 ***	−0.084 ***	0.526 ***
	(25.47)	(−3.71)	(18.85)
CPC membership		−0.046*	
		(−1.92)	
Road condition		0.052 ***	
		(3.46)	
Natural disaster		−0.022 *	
		(−1.82)	
Pseudo R^2	0.357	0.1636	0.3513
Observations	1166		1166

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Marginal effects rather than coefficients are reported. The validity of the instrumental variable was checked, including weak IV and overidentification tests.

5.2.4. Bivariate Probit Model

We utilized the bivariate probit model to explore the interdependence of the two dependent variables and to estimate whether $\rho_{\sigma\varepsilon}$ was significantly different from zero. The logic is that the correlation coefficient between two variables is equal to the sum of the causal and reverse-causal effects between these two decisions. If their interdependent relationship does exist, then we can further ascertain the causal effect of nonfarm work on the probability of straw incorporation adoption.

Concerning the determination of independent variables, we assumed that the two decisions are both influenced by cognitive ability, time and risk preferences, and variables at individual and family levels. However, the straw return decision will additionally be impacted by variables at the government policy level, such as propagation and punishment.

To test the significance of $\rho_{\sigma\varepsilon}$, we first report the results of the first-stage regression in Table 7. It is noteworthy that cross-sectional data can provide the relatedness of the regressor and regressed, which is the sum of the causal and reverse-causal effects between them. Under the guidance of our theoretical analysis, we interpreted the meaning of the coefficients.

Table 7. Empirical results of bivariate probit.

Variable	(1) Off-Farm Work		(2) Straw Return
Fluid cognitive ability	0.0290		0.0532
	(0.59)		(1.14)
Crystal cognitive ability	−0.106 **		0.136 **
	(−2.16)		(2.82)
Time preference	0.00517		−0.0277
	(0.50)		(−1.27)
Risk preference	−0.0323		−0.107
	(−0.24)		(−0.87)
Education	0.0557 **		−0.00907
	(2.59)		(−0.47)
Age	−0.0261 ***		0.00272
	(−5.43)		(0.58)
Gender	−0.238 **		−0.0513
	(−2.32)		(−0.56)
Health	0.197 **		0.187 **
	(2.88)		(3.16)
Family income	0.00150		0.00101
	(1.58)		(0.88)
Family number	0.0567		0.0791 **
	(1.63)		(2.56)
Land per capita	−0.0155 **		0.0127 **
	(−2.13)		(2.65)
Social network	0.0132		−0.130
	(0.12)		(−1.28)
Social trust	0.0118		0.180
	(0.10)		(1.53)
Social reputation	0.0377		0.0501
	(0.48)		(0.69)
Social participation	−0.178 **		0.265 ***
	(−2.53)		(3.71)
Propagation			0.197 ***
			(5.48)
Punishment			−0.102 **
			(−2.09)
Cattle	−0.516 ***		2.183 ***
	(−4.67)		(16.00)
Constant	−0.433		−2.972 ***
	(−0.70)		(−4.87)
Rho21		−0.252 ***	
		(−3.40)	
N	1166		1166

Note: *** and ** denote significance at 1% and 5% levels, respectively.

As reported in Table 7, education contributes to the choice to undertake off-farm work yet exerts no significant effect on increasing the straw return rate of farmers. It is more likely for a healthier and younger rural household to simultaneously choose nonfarm work and straw return. As a long-term investment, the adoption of straw returns is stifled by higher subjective discounted rates. A larger scale of arable land can deter farmers' from choosing to undertake off-farm work and facilitate the proliferation of straw returning through the scale economy channel in agricultural production. Additionally, the effects of crystal cognitive ability and social participation on straw incorporation are significantly positive, while they are both significantly negatively related to the choice to undertake nonfarm work.

The empirical findings demonstrate that different human capital factors have unique impacts on the decision to engage in nonfarm work or agricultural production. While education primarily has a positive influence on off-farm work, fluid cognitive ability is more important in agricultural production. Interestingly, there has been ongoing debate regarding why education has limited explanatory power in predicting farming productivity. This is because education is significant in respect of signaling abilities in the labor market, whereas small-scale farmers do not need to signal their productivity to themselves as they are self-employed.

In summary, Rho21 is significantly less than zero, which indicates that the decisions to undertake nonfarm work and adopt straw return are negatively related. Even if the two decisions are made jointly, we can still interpret the choice to undertake off-farm work as having a pronounced negative effect on the decision to engage in straw returning.

5.3. Robustness Check

To check the robustness of the previous conclusions, we deleted samples that reported that they adopted straw returns only because the local government required them to do so. If their choice to undertake straw return was compulsory, then undertaking both off-farm work and cognitive abilities do not have explaining power. After removing 149 subsamples, our sample was reduced to 1017. Using the new sample, we ran the stepwise regression, as shown in Table 8.

Table 8. Empirical results of stepwise regression of the probit model (new sample).

	(1)	(2)	(3)	(4)	(5)	(6)
Off-farm work	−0.136 ***	−0.208 ***	−0.204 ***	−0.212 ***	−0.086 ***	0.038
	(−3.19)	(−5.06)	(−4.97)	(−5.14)	(−2.58)	(0.51)
Fluid cognitive ability	0.037 **	0.014	0.014	0.013	0.001	0.011
	(2.33)	(0.90)	(0.92)	(0.85)	(0.04)	(0.81)
Crystal cognitive ability	0.018	0.024	0.023	0.021	0.027 **	0.027 **
	(1.14)	(1.63)	(1.56)	(1.41)	(2.27)	(2.25)
Time preference	−0.021 **	−0.013	−0.015 *	−0.014 *	−0.009	−0.009
	(−2.37)	(−1.64)	(−1.81)	(−1.69)	(−1.38)	(−1.45)
Risk preference	0.013	−0.016	−0.032	−0.031	−0.031	−0.005
	(0.30)	(−0.40)	(−0.78)	(−0.75)	(−0.95)	(−0.15)
Education	0.016 **	−0.003	−0.004	−0.004	0.002	0.002
	(2.48)	(−0.47)	(−0.62)	(−0.67)	(0.34)	(0.36)
Age		−0.007 ***	−0.007 ***	−0.007 ***	−0.001	−0.001
		(−4.97)	(−4.95)	(−4.97)	(−0.96)	(−1.00)
Gender		−0.067 **	−0.062 **	−0.062 **	−0.014	−0.015
		(−2.22)	(−2.04)	(−2.05)	(−0.57)	(−0.62)
Health		0.041 **	0.035 *	0.037 **	0.022	0.022
		(2.22)	(1.85)	(1.99)	(1.55)	(1.53)
Family income		0.002 ***	0.002 ***	0.002 ***	0.001 **	0.001 **
		(4.49)	(4.27)	(4.34)	(2.14)	(2.12)
Family number		0.025 **	0.025 **	0.024 **	0.011	0.010
		(2.47)	(2.46)	(2.39)	(1.30)	(1.27)
Land per capita		0.002	0.002	0.001	0.002 **	0.002 **
		(1.35)	(1.17)	(0.99)	(2.36)	(2.39)
Social network			−0.020	−0.015	−0.040	−0.041
			(−0.58)	(−0.45)	(−1.52)	(−1.57)
Social trust			0.079 **	0.073 **	0.086 ***	0.091 ***
			(2.15)	(1.97)	(2.96)	(3.14)
Social reputation			0.002	−0.004	0.006	0.003
			(0.09)	(−0.18)	(0.35)	(0.15)
Social participation			0.012	0.013	0.046 ***	0.046 ***
			(0.55)	(0.65)	(2.83)	(2.86)
Propagation				0.025 **	0.030 ***	0.030 ***
				(2.25)	(3.35)	(3.39)
Punishment				−0.020	−0.020	−0.021
				(−1.22)	(−1.58)	(−1.63)
Raising cattle					0.535 ***	0.534 ***
					(30.74)	(30.88)
Work * Fluid						−0.056 *
						(−1.71)
Work * Risk						−0.152 *
						(−1.73)
Pseudo R^2	0.0213	0.0942	0.0994	0.1038	0.3983	0.4031
Observations	1017	1017	1017	1017	1017	1017

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. Marginal effects rather than coefficients are reported.

Compared with the results of Table 3, Table 8 reports identical outcomes. However, two noticeable differences can still be found. The first difference is that the coefficient of off-farm work on straw return is a little smaller in Table 8, because the deleted subsample comprised only straw-return adopters. For the same reason, the coefficients of the two interaction terms also decreased slightly. The second difference is displayed in the change in Pseudo R^2. Taking regression (6) as an example, Table 8 seems to have a higher Pseudo R^2 value than Table 4. We therefore conclude that the deletion of compulsory adopters in fact increases the explaining power of the probit model. In summary, Table 8 indicates that most of the farmers in Liaoning province can freely choose whether to adopt straw return or not, and off-farm work does have a significant hindering effect on the proliferation of straw return.

6. Discussion

6.1. New Findings Compared to Previous Studies

Unlike previous studies, we have presented new findings in the three following aspects.

First, unlike most of the research that neglects the joint nature between the choice to undertake off-farm work and the adoption of straw return, we demonstrated that the two decisions are negatively related. This finding means that when making choices, farmers in fact jointly evaluate the benefits of farm and off-farm activities. Nonetheless, in most developing countries, undertaking off-farm activities is common, which can significantly impact the process of technology proliferation.

Second, we have contributed to the development of human capital theory by finding that human capital variables such as fluid cognitive ability, crystal cognitive ability, education, and health play different roles in the joint decisions to undertake off-farm and farm activities. Compared with other dimensions of human capital, education levels endow farmers with comparative advantages in terms of off-farm work by providing a screening tool. In contrast, cognitive abilities, especially fluid cognitive ability, matter more in the dynamic changes of agricultural production.

Thirdly, our findings support the fact that not all agricultural technology adoption is sensitive to income or financial constraints. On the contrary, the proliferation of certain technologies, such as straw return, is more susceptible to time allocation constraints. Hence, we believe that our empirical findings can be generalized to most developing countries where the adoption of straw return is mostly time-consuming; hence, the “lost labor effect” will dominate over the “income-increasing effect”.

6.2. Research Deficiencies and Prospects

Although this study offers a new perspective by utilizing a simultaneous decision approach, two shortcomings can still be identified.

First, we developed a theoretical framework to measure risk and time preferences by asking respondents to choose from the items listed instead of using experimental methods. Some researchers argue that risk and time preferences should be tested in the same questionnaire with real money incentives; otherwise, the results obtained from the tests will be biased [41]. Since we conducted more than 1100 interviews, the total cost of using the money incentive method would be more than CNY 100,000. For this reason, we gave up the experimental method and accepted the probably biased measured variables.

Second, both simultaneous and self-selection bias can cause endogeneity, which calls for panel data to properly solve this problem. However, it is difficult to survey highly mobile farmers at different times who intend to migrate. In this environment, cross-sectional data require more complicated empirical methods, and for this reason, we utilized different models to reach a relatively robust conclusion.

Based on the research deficiency analysis, future research should endeavor to ensure that the measurement of relevant variables is more accurate and create longitudinal data for more strict empirical analysis.

6.3. Policy Implications

Based on our empirical findings, four recommendations can be proposed.

The first valuable policy implication of effectively intervening in the proliferation of agricultural technologies is to increase agricultural specialization. Concrete policies include the promotion of transferring arable lands among farmers and increasing the efficiency of human capital accumulation. Since farmers' decisions are made in the context of allocations between nonfarm and farming activities rather than farm operations alone, edges in farming may be generated through the mechanisms of economies of scale and accumulated knowledge in planting. Scale economies in agricultural production and livestock breeding will cultivate more professional farmers who put little energy into nonfarm activities.

Secondly, the modernization of agricultural production entails the enhancement of human capital levels; thus, it is necessary to adopt aggressive training programs to smooth the channels of learning by doing. In a changing economic environment, farmers must continually make allocative decisions, thus strengthening the role of cognition in obtaining, processing, and updating relevant information concerning the adoption of new technologies. Compared with fluid cognitive ability, crystal cognitive ability is easier to cultivate. In addition, forming more cohesive social relations among farmers can compensate for the dysfunction of formal institutions by reducing the cost of information gathering through mutual and social learning.

Thirdly, we propose that in addition to providing subsidies to encourage farmers to adopt straw-returning practices, targeted strategies should prioritize cultivating farmers' inclination towards long-term investment. Specifically, these strategies should encompass comprehensive training programs for smallholder farmers, enabling them to fully comprehend the long-term benefits and develop patience in resisting the allure of immediate consumption. It is worth noting that low-income households tend to exhibit risk aversion and present bias, which often leads to underinvestment in profitable long-term projects. Therefore, alongside offering loans and subsidies, it is crucial to effectively communicate the tangible advantages of straw returning, such as increased crop yields and reduced agricultural production risks, to farmers in a timely manner.

Lastly, considering the low levels of cognitive abilities for most of the farmers, a portfolio of incentive policies and instructions should be adopted to realize the effect of straw return on the protection of arable land. When several new production methods are combined, it is more difficult for farmers to find the best practices. Taking the proliferation of the no-tillage farming method as an example, the government should not only propagate the concrete method of straw return but also instruct farmers to alternate fertilization and irrigation practices to achieve the best effects in arable land protection.

7. Conclusions

Based on a sample of 1166 maize-planting farmers, we estimated the causal effect of off-farm work on the adoption of straw return. Our conclusions mainly include three points:

First, through different empirical methods, our research robustly demonstrates that undertaking nonfarm work has a significant negative effect on the decision to adopt straw returning. Instead of supporting the income-increasing effect, our research identified a strong effect of the lost-labor hypothesis. Due to limited time resources, nonfarm employment substitutes for the adoption of straw incorporation by reducing the time allocated to agricultural production. Our conclusion suggests that although nonfarm employment provides an important source of financial compensation for farmers, the lost-labor effect reduces the diffusion of time-consuming agricultural practices.

Second, cognitive abilities matter in the joint decision to undertake off-farm work and straw returning, with fluid and crystal cognition playing different roles. Specifically, the fluid cognitive ability of a rural household significantly contributes to the proliferation of straw returning, while crystal cognitive ability significantly deters the decision to undertake nonfarm work by providing a comparative advantage in agricultural production. This conclusion confirms the theory that fluid cognitive ability can speed up the process of adopting new production practices by increasing learning and updating efficiency, whereas crystal cognitive ability can increase agricultural specialization by creating a competitive edge in farming.

Third, mechanism analysis shows that off-farm work not only interacts with fluid cognitive ability and risk preference but also exerts indirect effects through mediators such as raising cattle, the scale of arable land, and health. For the interaction effect, we found that more intelligent and risk-tolerant farmers undertaking off-farm work will have additional negative impacts on the likelihood of adopting straw return. Furthermore, the choice to undertake off-farm work will decrease the probability of raising cattle, downscale arable land, and reduce the likelihood of adopting straw return further.

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