Adoption of Multiple Soil Fertility Management Practices and Its Impact on Farm Performance in Rural China

Abstract

The adoption of soil fertility management practices (SFMPs) has become an important issue in the development economies, especially as a way to tackle land degradation, erosion, and low agricultural productivity. This study analyses the factors that facilitate or impede the probability and extent of adoption of multiple SFMPs as well as the performance effects, using farm survey data of 773 vegetable producers in rural China. Multivariate and ordered probit models are applied to the modeling of adoption decisions by farm households facing multiple SFMPs, which can be adopted in various combinations. A multinominal endogenous switching regression model is used to investigate the impact of SFMP adoption on farm productivity. The results show that: (1) the adoption of straw returning and advanced irrigation have substitution effect, and subsoiling practice is significantly correlated to straw returning and soil testing; (2) both the probability and the extent of adoption of SFMPs are influenced by many factors: household's education, cadre membership, cooperative and training participation, social capital and individual awareness; (3) farms' productivity is increasing with the intensive adoption of SFMPs. These results imply that policymakers should seek to promote local institutions and training providers, increase household education and awareness, and strengthen social networks in order to improve the adoption of SFMPs.

Keywords: soil fertility management; multivariate probit; multinominal endogenous switching regression, simultaneous adoption

JEL code: O13, Q16

1. *Introduction*

The pressure on land resources in the world is currently enormous, and developing countries in particular are facing serious challenges. Soil fertility is a critical solution that involves the soil's ability to support plant growth by providing essential nutrients, favorable physical, chemical, and biological properties, and a habitat for plant growth. Fertile soils primarily provide food, which is crucial to achieving the zero-hunger target set by the FAO, as well as economic implications on poverty eradication and economic growth. Soil fertility management practices (SFMPs) were primarily brought about in the 1950s by the Green Revolution and developed in the 1980s by the International Center for Soil Fertility and Agricultural Development (IFDC) to decrease soil, water, and air pollution and promote sustainable ecological development. Nowadays, it was widely developed around the world. China, with high population pressure and small landholding per capita, has paid much attention in recent years to the adoption of SFMPs to tackle land degradation, erosion, and low agricultural productivity.

Farm technical efficiency is a measure of how well farmers use inputs such as labor, capital, and land to produce a given output. The impact of SFMPs on farm technical efficiency has been assessed in several studies. For example, Geta et al. (2013) used data from 385 randomly selected farmers to evaluate the positive and significant impact of integrated soil fertility management on maize smallholder productivity and efficiency in southern Ethiopia. Adolwa et al. (2019) used a counterfactual model to assess SFMPs' impact on yields and total household incomes using farm household data from Northern Ghana and Western Kenya. Their analyses revealed that ISFM adoption led to an increase in maize yields however, did not improve yields. Ngango and Seungjee (2021) applied cross-sectional data collected from 360 farmers in Rwanda to analyze the adoption of small-scale irrigation technologies and their impact on land productivity and found a significant impact by conducting a propensity score matching technique.

Additionally, the adoption of SFMPs has been shown to be influenced by different factors. For instance, Martey and Kuwornu (2021) used data covering smallholder farmers in Ghana and found that a range of socio-economic and farm-related factors including education, household size, the slope of farmland, distance to extension services significantly influenced farmers' adoption of SFMPs by using Poisson and Negative Binomial Regression Models. In the research of 360 smallholder farmers in Rwanda, Ngango and Seungjee (2021) added new evidence that extension services and awareness significantly played a role in farmers' adoption of SFMPs. Farm size was found to be an important factor that facilitated farmers' adoption of SFMPs by Katengeza et al. (2019) in the research of a four-round panel dataset collected from households in six Malawi districts over nine years. Considering the policy environment and land quality in different regions, research on the adoption of SFMPs needs to be tailored to local conditions. Also, since a lack of knowledge, inadequate access to resources and technology, and limited financial capacity, many farmers are still relying on conventional farming methods in rural China.

To address these challenges and promote the adoption of sustainable SFMPs, this paper aims to explore factors that facilitate or impede the probability and extent of adoption of multiple SFMPs as well as the performance effects, using farm survey data of 773 vegetable producers in rural China. We include four practices including advanced irrigation, subsoiling, straw returning, and soil testing. It is crucial to know the adoption pattern of SFMPs in rural China and if the current SFMPs enhance or threaten the productivity of land use.

The contributions of our article to the empirical literature are as follows. First, the adoption of multiple SFMPs in the farming context, ranging from livestock to food, is well studied, but research on vegetable production is, in general, scarce. This study attempts to close this gap. Second, instead of roughly classifying SFMP adopters, we consider the nature of interrelationships among the set of practices and jointly analyze farmers' decision to adopt multiple SFMPs and help policymakers and development practitioners to define their strategies for promoting agricultural practices. Third, a more specific comparison of technical efficiencies between SFMP adopters of different extents and non-adopters provides new evidence for our understanding of the impact of SFMPs on farm performance.

2. *Soil Fertility Management Practices and theoretical framework*

Of the several SFMPs promoted, we focus on four considering data availability, with each practice discussed below.

Irrigation. The technical principle of fertigation is based on the law of vegetable water and fertilizer needs, through the drip irrigation method of water and fertilizer evenly, in the right amount, accurately and directly to the surface near the roots of the crop, and then infiltrated to the root system area, so that the root system activity area of the soil to maintain the best water and nutrient supply state. This practice has cracked the problem of large losses of irrigation water and fertilizer caused by the mismatch between water and fertilizer supply and vegetable demand in traditional planting methods.

Straw returning. Straw returning to the field is a method of applying straw that is not suitable for direct feed into the soil directly or after being piled up and decomposed. After the vegetable stalks are crushed and returned to the field, farmers need to sprinkle bacterial fertilizers and bury the crushed stalks in the ground through deep plowing. After a period of maturity and decomposition, they can be transformed into organic matter and available nutrients to fertilize the soil. This practice can not only eliminate the air pollution caused by straw burning but also save human and financial resources.

Subsoiling. Subsoiling is a method of deep plowing that loosens the soil without overturning the soil layer with loosening tools such as subsoiling shovels or chisel plows. It can thicken the living soil layer, increase water permeability, increase soil water storage capacity, reduce surface runoff, and save and utilize natural precipitation more. Thickening the living soil layer can also promote the development of crop roots and improve soil water use efficiency. This practice is beneficial to the gas exchange of the soil, promotes the activation of microorganisms and the decomposition of minerals, and improves soil fertility

Soiling testing. The practice of soil testing and formula fertilization aims to address the mismatch between the demand for crop fertilizers and the supply of soil fertilizers. It involves targeted supplementation of nutrient elements required by crops, including those that are lacking, in order to achieve a balanced nutrient supply and meet crop needs. The ultimate goal is to improve fertilizer utilization, reduce dosage, and enhance crop yield and quality, while saving labor, reducing costs, and increasing income.

Considering the nature of each practice, the adoption of SFMPs could be a technical efficiency driver in many aspects: First, SFMPs can also reduce input costs such as fertilizer, pesticides, and irrigation. By maintaining soil fertility, the need for costly inputs such as synthetic fertilizers and pesticides can be minimized, resulting in lower costs and higher profits. Second, by maintaining soil fertility, soil health can also be improved, which leads to better crop growth and reduced crop losses. Healthy soils can also improve water retention, which reduces the need for irrigation and saves on water costs. Third, SFMPs can improve soil structure, which can reduce erosion and increase soil water-holding capacity, leading to more efficient use of resources and a reduction in the need for expensive inputs such as irrigation and soil amendments. Fourth, SFMPs can contribute to long-term sustainability by maintaining soil health and reducing the negative impacts of agriculture on the environment, which increases farm productivity and profitability over time.

3. Data

The data was obtained from the questionnaire survey in Shouguang city of China, located in the coastal plain area of north-central Shandong Province. Shouguang is named "the hometown of vegetables in China" by the State Council and has the largest wholesale vegetable production market in China. Relying on the superior topography and climate, stable market environment, and government support, the introduction and promotion of advanced technologies started in Shouguang. The vegetable planting area in Shouguang City has grown to 600,000 mu, with an annual output of 4.5 million tons, and 78,000 farmers are directly engaged in vegetable production.

We used Probability Proportional Sampling and Random Sampling methods to survey in 2019, that is, we randomly selected 6 towns (Figure 1), and then randomly selected a similar number of farmers in each town. We had face-to-face interviews with farmers to finish the questionnaire. The contents of the questionnaire cover farm income and expenditure, assets, capital, household characteristics, and detailed information about production practices. Finally, we got 773 observations which are used in this research for analysis.

The variables selection and definition are interpreted in Table 1 including variables in the MVP and MESR models. The inclusion of variables in the analysis and model specification is primarily based on theoretical frameworks and past empirical adoption literature (Aryal and Holden, 2012; Erenstein and Farooq, 2009; Feder and Umali, 1993; Kassam et al., 2009; Kassie et al., 2013; Pender and Kerr, 1998). A description of explanatory variables and a hypothesis about their effects on the dependent variable is given below.

Householder characteristics

Household characteristics include the major characteristics of the household head (such as literacy status, age, and gender), which often influence technology adoption decisions (de Janvry et al., 1991). Household heads who are literate, with at least a primary education, are more likely to have non-farm income and better access to and processing of new information, which enhances their ability to acquire, absorb, and adopt new technology (Chander and Thangavelu, 2004). Farm technology adoption is typically part of an overall household strategy to improve livelihoods, so the literacy status of the household head can affect it. The gender of the household head can also impact technology adoption decisions, as men and women may have different preferences for technologies.

Household and farm characteristics

The adoption of new technology may be hindered by a high dependency ratio as it generally requires more active labor inputs. Additionally, farmers with a high number of non-active family members may not be able to afford the cost of implementing SFMPs. To account for farm characteristics that may influence technology adoption decisions, we control for the factors such as farmland size and distance to market. For instance, distant farms may be costly to transport inputs to and difficult to monitor, which could make farmers less inclined to adopt new technology. Various studies have demonstrated a positive relationship between farmland size and technology adoption since households with larger farms can allocate a portion of their land to try out new technology, unlike those with smaller farms. Furthermore, some large facility technologies necessitate economies of scale to ensure profitability. However, certain studies have indicated that farm size may have a negative impact on the adoption of new agricultural technologies, particularly in the case of labor-intensive or land-saving innovations. As a result, the sign of the coefficient on the farmland size variable is uncertain.

Financial characteristic

The financial variable in this study includes off-farm income and farmers' attitudes to their income. To account for the impact of off-farm income on the adoption of SFMPs, we considered the primary sources of household income, such as working in a factory or a government job. Family size was measured by the number of household members. To assess farmers' attitudes towards their income, we created a dummy variable that equals 1 if the household is satisfied with its income and 0 if it is not. The adoption of new agricultural technology is influenced by economic incentives, although the extent of its impact can be complex and uncertain. Households with alternative sources of income may be better able to adopt new technology since they may have better access to information about it or the ability to finance investments. Allocating household labor to activities other than agriculture, which provide higher returns, may decrease attention paid to agricultural activities, such as time and energy.

Information source

This study considers cooperative membership, training, and internet access as an information source that impacts SFMPs adoption. Mostly, cooperatives provide technical training and education that can alleviate farmers' information constraints and increase their level of awareness of new technologies. Training helps to reduce farmers' risk expectations and increase their confidence in adopting SFMPs in vegetable production. The Internet can reduce farmers' information search costs and enable them to access technology information in a timely and convenient manner.

Social capital

The peer effect is taken as social capital. In a social environment with complex local relationships such as rural China, the influence of farmers' social capital on their behavioral decisions is even more pronounced. Due to the reciprocal motivation among members, strong ties can reduce the cost of acquiring and analyzing information for farmers and provide opportunities for mutual learning, communication, and assistance when adopting SFMPs.

Awareness

The technology acceptance model proposes that adoption behavior and the extent of consumer acceptance are influenced by the attitude which includes perceived ease of use and usefulness of a technological tool. Since it is commonly assumed in agricultural economic models that farmers maximize profits, we take farmers' attitudes towards the profit of technology adoption to proxy usefulness.

4. *Methodology*

Farmers face multiple SFMPs which can be adopted in various combinations, and their adoption decision is not randomly assigned, which may be influenced by both observed and unobserved factors (Dorfman, 1996). To allow for the potential endogeneity associated with unobserved heterogeneity and simultaneous adoption decisions, our empirical framework includes three parts: first, farmers' choice of interrelated SFMPs is modeled using a multivariate probit (MVP) model, and the determinants of the extent of combinations of SFMPs adopted are investigated in an ordered probit (OP) model. Second, to explore the impact of SFMPs adoption on farm productivity, we apply the multinominal endogenous switching regression (MESR) model following Dubin and McFadden (1984) and Bourguignon et al. (2007) to correct selection bias, which holds the explanatory variables and the error term uncorrelated and lead to unbiased results. In the third stage, we estimate the average treatment effect (ATT) of SFMPs adoption on farms' productivity by comparing the actually observed outcomes and their respective counterfactual expected outcomes between non-adopters and adopters.

4.1 Multivariate probit model

When using a single-equation statistical model, the decision to adopt one SFMP does not affect the likelihood of adopting another. However, the MVP approach models the impact of a set of explanatory variables on each of the different practices simultaneously, while accounting for the potential correlation between unobserved disturbances and the relationship between the adoption of different practices (Belderbos et al., 2004). We hypothesize that farmers' decision to adopt these SFMPs is interdependent. This hypothesis is valid if the error terms of the multiple decision equations are significantly correlated. One potential source of correlation could be complementarity (positive correlation) or substitutability (negative correlation) between different practices (Belderbos et al., 2004). Failing to account for unobserved factors and interrelationships among adoption decisions for different practices can result in biased and inefficient estimates (Greene, 2008).

The observed outcome of SFMP adoption can be modeled following a random utility formulation. Consider the i[th] farm household (i=1,…, N) facing a decision on whether or not to adopt the available SFMP. Let U_0 represent the benefits to the farmer from traditional management practices, and let U_k represent the benefit of adopting the kth SFMP: where k denotes choice of irrigation (I), straw returning to farm (R), subsoiling (S), and soil testing (T). The farmer decides to adopt the kth SFMP if Y_k=U_k-U_0>0. The net benefit (Y_k) that the farmer derives from the adoption of kth SFMP is a latent variable determined by observed household characteristics, other control variables, locational dummy variables (*Gucheng/Hualong/Luocheng/Sunjji/Tianliu*), and the error term:

$$Y_{ik} = X_i\beta_k + \varepsilon_i \tag{1}$$

Using the indicator function, the unobserved preferences in equation (1) translate into the observed binary outcome equation for each choice as follows:

$$Y_{ik} = \begin{cases} 1, & if\ Y_{ik} > 0 \\ 0, & Otherwise \end{cases} \tag{2}$$

For these SFMPs, we hypothesize that the decisions to adopt them are interdependent. This hypothesis is valid if the error terms of the multiple decision equations are significantly correlated. In the multivariate model, where the adoption of several SFMPs is possible, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters) where: (uI; uS; uR; uT): MVN (0; Ω) and the symmetric covariance matrix Ω is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{IR} & \rho_{IS} & \rho_{IT} \\ \rho_{RI} & 1 & \rho_{RS} & \rho_{RT} \\ \rho_{SI} & \rho_{SR} & 1 & \rho_{ST} \\ \rho_{TI} & \rho_{TR} & \rho_{TS} & 1 \end{bmatrix} \quad (3)$$

The off-diagonal elements in the covariance matrix, which represent the unobserved correlation between the stochastic components of various SFMP types, are of particular interest. This assumption generates an MVP model that jointly represents decisions to adopt a particular farming practice. The specification with non-zero off-diagonal elements allows for correlation across the error terms of multiple latent equations, representing unobserved characteristics affecting the adoption of alternative SFMPs.

4.2 Ordered probit model

In addition to the probability of adopting SFMPs, it is important to consider the level of adaptation of these practices. Following D'Souza et al. (1993) and Wollni et al. (2010), we use the number of SFMPs adopted as our dependent variable to measure the extent of adoption. The ordered probit model allows to examine the factors that influence the adoption of a combination of practices (number of practices), as well as individual practice. Additionally, the variables that affect the probability of adoption may have different effects on the intensity of adoption.

We assume that the i[th] farm household decides to choose several SFMPs based on the maximization of an underlying utility function (h_i^*).

$$\mathrm{h}_i^* = \mathrm{Z_i}\gamma + \mathrm{u_i} \quad (4)$$

where z are vectors of observed variables for the SFMPs frequency choice equation. γ represents unknown parameter vectors to be estimated and $\mathrm{u_i}$ represents unobserved effect.

Since the utility level of an individual farmer (h^*) is unobserved, it is assumed to be related to the latent variable h_i which indicates the farmer's observed choice of a combination of practices M (M=1, …, 5) as:

$$h_i = \begin{cases} 1 \; if \; \mathrm{h}_{i1}^* > \max_{k \neq 1}(\mathrm{h}_{ik}^*) \; or \; \mathrm{u_{i1}} < 0 \\ \dots \\ M \; if \; \mathrm{h}_{iM}^* > \max_{k \neq M}(\mathrm{h}_{iM}^*) \; or \; \mathrm{u_{iM}} < 0 \end{cases} \quad (5)$$

Assuming that u_{ij} are identically and independently Gumbel distributed, the selection model leads to a multinomial logit model where the probability of adoption extent j (Pr_{ij}) is (McFadden, 1973):

$$\mathrm{Pr}_{ij} = \mathrm{Pr}(\varepsilon_{ij} < 0 | \mathrm{z}_i) = \frac{\exp(\mathrm{z}_{1i}\gamma_{ij})}{\sum_{j=1}^{J}(\mathrm{z}_{1i}\gamma_{ij})} \quad (6)$$

The parameters of the latent variable model can be estimated by maximum likelihood.

4.3 Endogenous switching regression model

An endogenous switching regression model is used to investigate the relationship between the outcome variable (technical efficiency) and SFMPs adoption in which farmers were partitioned into different regimes. The outcome equation for each possible combination of practices (Regime j) is given as:

$$\begin{cases} Regime\ 1: Q_{i1} = \mathrm{z}_{2i}\alpha_{i1} + \mathrm{u}_{i1} \quad if\ I = 1 \\ \quad\quad\quad\quad\cdots \\ Regime\ J: Q_{iJ} = \mathrm{z}_{2i}\alpha_{iJ} + \mathrm{u}_{iJ} \quad if\ I = J \end{cases} \tag{7}$$

where Q_{ij} is the outcome variable of the i^{th} farmer in regime j, β_{ij} is the corresponding vector coefficient to the factors influencing the outcome, and the error terms (u_{ij}) are distributed with $\mathrm{E}(\mathrm{u}_{ij}|\mathrm{z}_{1i},\ \mathrm{z}_{2i}) = 0$ and $\mathrm{var}(\mathrm{u}_{ij}|\mathrm{z}_{1i},\ \mathrm{z}_{2i}) = \sigma_j^2$. If the η_{ij} and u_{ij} are not independent, OLS estimates in Eq. (9) will be biased. Consistent estimation of α_{ij} requires the inclusion of the selection correction terms of the alternative choices in Eq. (9). The DM model assumes the following linearity assumption:

$$E\left(\mathrm{u}_{ij} \middle| \eta_{i1}, \dots, \eta_{iJ}\right) = \sigma_j \sum_{m \neq J}^{J} r_j\left(\eta_{\mathrm{im}} - \mathrm{E}(\eta_{\mathrm{im}})\right) \tag{8}$$

with $\sum_{j=1}^{J} r_j = 0$ (by construction, the correlation between u_{ij} and η_{ij} sums to zero).

Using this assumption, the equation of the multinomial ESR in Eq. (7) is specified as:

$$\begin{cases} Regime\ 1: Q_{i1} = \mathrm{z}_{2i}\beta_{i1} + \sigma_1\hat{\lambda}_1 + \varepsilon_{i1} \quad if\ I = 1 \\ \quad\quad\quad\quad\cdots \\ Regime\ J: Q_{iJ} = \mathrm{z}_{2i}\beta_{iJ} + \sigma_J\hat{\lambda}_J + \varepsilon_{iJ} \quad if\ I = J \end{cases} \tag{9}$$

where σ_j is the covariance between u_{ij} and η_{ij}, and λ_j is the inverse Mills ratio computed from the estimated probabilities in Eq. (6) as follows:

$$\lambda_j = \sum_{m \neq J}^{J} \rho_j \left[\frac{\widehat{\Pr}_{im}\ln(\widehat{\Pr}_{im})}{1-\widehat{\Pr}_{im}} + \ln\left(\widehat{\Pr}_{ij}\right)\right] \tag{10}$$

where ρ_j is the correlation coefficient of u_{ij} and η_{ij} , and ε_{ij} are error terms with an expected value of zero.

The above framework can be used to examine the average treatment effects (ATT) by comparing the expected incomes of high-extent adopters with the counterfactual incomes of non-adopters. Following Carter and Milon (2005) and Di Falco et al. (2011), we compute conditional expectations for each outcome variable in the actual and counterfactual scenarios as follows:

Actual outcomes observed in the sample:

$$E\begin{cases} E(Q_{i2}|\mathrm{I} = 2) = \mathrm{z}_{2i}\beta_{i2} + \sigma_1\hat{\lambda}_2 \\ \quad\quad\quad\quad\cdots \\ E\left(Q_{iJ}\middle|\mathrm{I} = \mathrm{J}\right) = \mathrm{z}_{2i}\beta_{iJ} + \sigma_J\hat{\lambda}_J \end{cases} \tag{11a}$$

Counterfactual outcomes:

$$\begin{cases} E(EE_{i1}|\mathrm{I} = 2) = \mathrm{z}_{2i}\beta_{i1} + \sigma_2\hat{\lambda}_2 \\ \quad\quad\quad\quad\cdots \\ E(EE_{i1}|\mathrm{I} = \mathrm{J}) = \mathrm{z}_{2i}\beta_{i1} + \sigma_J\hat{\lambda}_J \end{cases} \tag{11b}$$

The use of these conditional expectations allows us to derive unbiased estimates of the average treatment effects on treated (ATT):

$$ATT = E\left(EE_{ij}\middle|\mathrm{I} = \mathrm{j}\right) - E(EE_{i1}|\mathrm{I} = \mathrm{j}) = \mathrm{z}_{2i}\left(\beta_{ij} - \beta_{i1}\right) + \hat{\lambda}_j\left(\sigma_j - \sigma_1\right) \quad j = 2, \dots, J \tag{12}$$

The first term on the right-hand side of Eq. (12) represents the expected change in farms' mean outcome if their characteristics had the same return as other regime farms. The second term is the selection term that captures all potential effects of difference in unobserved variables.

5. *Results*

5.1 Conditional and unconditional adoption

The joint and marginal probability distribution of farms for the four SFMPs is presented in Table 2. Of the 773 farms considered in the analysis, about 77.1% benefited from one or more SFMPs although all four SFMPs were applied in only 11 farms. Irrigation was the most common SFMP adopted by 23.9% of the sample farms. It was used in combination with subsoiling on 15.1% of farms and in combination with subsoiling and soil testing on 6.7% of farms. Subsoiling alone was adopted on 11.8% of farms, in combination with soil testing on 3.2% of farms and jointly with irrigation and straw returning on 3% of farms. 2.9% of the farms received only the soil testing practice and 2.7% benefited from the adoption of both soil testing and irrigation. The number of straws returning adopters was the least 1.3%. Similarly, 1.7% of farms used straw returning and subsoiling jointly, and only 0.1% adopted the combination of straw returning and soil testing. There were 22.9% of farmers that produce conventional farms without any practices adoption.

Although the statistics on the joint and marginal probabilities provide interesting results, the sample unconditional and conditional probabilities of adoption also provide an indication of the existence of possible interdependence across the four SFMPs. The results suggest that the adoption of one practice increases the likelihood of adopting others. For example, the unconditional probability of a farm adopting irrigation is 55.1% and increases to 61.4% (straw returning), 59.7% (subsoiling), and 60% (soli testing) conditional on the adoption of one practice, respectively. The same pattern holds for the other practices. The conditional probabilities show that the combination of two practices further increases the likelihood of adopting a third practice. For instance, the probability of irrigation adoption increases from 55.1% to 65.6% when farmers adopt both subsoiling and soil testing. The same is true for other combinations of two practices. The conditional probability of farmers adopting irrigation on the other three practices is 57.9%, which is the highest, followed by 32.4% for soil testing adoption and 17.5% for straw returning adoption. Interestingly, the unconditional probability of adopting subsoiling is 100% when farmers adopt all three of the other practices, indicating a strong relationship between subsoiling and the other practices.

5.2 Regression Results

5.2.1. Adoption decisions: MVP model results

The results of the MVP model are estimated through the maximum likelihood method on farm-level data shown in Table 3. The data was fitted well by the model, as indicated by the Wald test [$\chi^2(88) = 862.93$, P = 0.00], which rejects the hypothesis that all regression coefficients within each equation are jointly equal to zero. Additionally, the likelihood ratio test [$\chi^2 2(6) = 35.06$, P = 0.00], reject the null hypothesis that the error term covariances across equations are not correlated, reflecting the heterogeneity in the adoption of SFMPs. Thus, a separate analysis of each SFMP variable is supported rather than aggregating them into a single variable. The results in Table 4 indicate that there is a significant negative correlation coefficient of -0.14 between irrigation and straw returning, suggesting a substitution effect between the two practices. Subsoiling practice is significantly correlated to straw returning (0.13) and soil testing (0.33), suggesting that adoptions of SFMPs are interrelated.

The MVP model results reveal that the gender of the household has a significant impact on SFMPs adoption with a different sign. That is, male farmers are more likely to adopt irrigation and female farmers have a higher probability to adopt subsoiling and soil testing. The result underscores the important role women play in agriculture and technology adoption decisions in developing countries. One implication is that with education improved, female farmers play a more important role in technology adoption decisions. Households who have a membership of the cadre positively influence the adoption of straw returning and subsoiling, because they more trust in government and have a better understanding of the importance of SFMPs.

Famers' education level has a positive impact on the adoption of irrigation and soil testing. Farmers with a higher education level tend to have a better understanding of the benefits of SFMPs adoption in increasing crop yield and quality. Education can also improve farmers' ability to access more sources of information and make informed decisions. Farmers with higher education may be better able to communicate with agricultural experts and other farmers about irrigation and soil testing methods. They can express their needs and concerns more effectively and collaborate with others to find solutions to common problems.

Off-farm income increases the chance of farmers adopting irrigation and soil testing, reflecting the capacity to purchase external inputs and to cope with greater risk. These investments may include purchasing irrigation equipment, hiring technical experts to carry out soil tests, and purchasing fertilizers and other soil conditioners. Off-farm income can also reduce the financial risks associated with investing in SFMPs. Farmers with off-farm income may be more willing to take risks in adopting new practices because they have a more stable source of income to fall back on in the event of crop failure or other setbacks.

The MVP model results also underscore the important role of cooperative play in the adoption of subsoiling and soil testing. Cooperatives can provide farmers with access to resources, such as specialist equipment or technical knowledge. Farmers who join cooperatives may have the opportunity to learn from other members who have adopted subsoiling and soil testing practices, which can help build trust and confidence in these practices. Cooperatives can also create economies of scale, making the adoption of SFMPs more cost-effective for individual farmers.

The hypothesis that social learning positively affects the probability of adoption of SFMPs is confirmed. The results also reveal that households that have training are more likely to adopt soil testing because this practice is relatively knowledge-intensive and requires considerable management. Farmers using the internet are more likely to adopt straw returning. This suggests that improving ICT infrastructure and encouraging farmers' awareness of learning to use ICT adoption is important in facilitating SFMPs adoption. The internet provides farmers with access to a wide range of information including using the right equipment, the timing of the practice, and how to manage the soil to maximize its benefits. The internet can also facilitate knowledge sharing between farmers and experts by accessing forums, social media groups, and other online platforms.

Land size has a significant positive impact on the adoption of irrigation and straw returning. Larger farms typically have more resources available which make it more feasible for farmers to adopt practices that require significant investments in time, labor, and equipment. They also may be able to afford to purchase or rent specialized equipment and hire technical experts to advise them on the best practices for straw returning and irrigation due to benefit from economies of scale in production. In practice, a farmer producing large-size farms is more likely to engage in long-term planning and investment in sustainable practices with access to financial resources and land tenure security.

5.2.2 Adoption extent: ordered model results

Table 5 shows the results from ordered probit models. The Chi-squared statistic for the ordered probit model is statistically significant [$\chi^2(20)$ =259.55, p=0.00] at less than 1% significance level, indicating that the joint test of all slope coefficients equal to zero is rejected. Results show that the number of SFMPs adopted increases with education. As in the adoption decision, the farmers' education level has a significant and positive effect on the level of SFMP use. Each additional year of education increases the probability of adopting more than two SFMPs by 0.4%. The membership of the cadre has a significant and positive impact on the number of SFMPs adopted. Farmers who are cadre in the village are 7% more likely to adopt more than two SFMPs.

Social capital and network variables have significant and positive effects on the number of SFMPs used, with varying marginal probabilities. If a household is a member of a cooperative, the probability of adopting more than two SFMPs increases by 6.7%. Consistent with the probability of SFMP adoption, a farmer's participation in training and peer effect plays an important role in the number of SFMPs adopted. Households who have a membership of village leaders positively influence the adoption of SFMPs since village leaders may have a better understanding of the potential benefit of SFMPs and may have access to resources that can facilitate the adoption.

In the study area, households having awareness and finding the SFMP adoption profitable, are 1.6% more likely to adopt two or more practices. Farmland size has a statistically significant, but small positive marginal probability effect (0.6%) for adopting more than two SFMPs. This result is consistent with the positive effect of farmland size on the likelihood of adoption of SFMPs.

5.2.3 Average treatment effect: endogenous switching regression results

Table 6 presents the average treatment effects in terms of the adoption of different numbers of SFMPs. The simple comparison of mean technical efficiencies[1] among different combinations is misleading because it does not account for both observed and unobserved factors that may influence the outcome variable (technical efficiency). To estimate the true average adoption effects for households that did (not) adopt, the mean value of technical efficiency of (non-)adopted farms are compared with the mean value of technical efficiency if the farm households had not (or had) adopted SFMPs. We do this by applying Eq. (12) to estimate ATT.

[1] We adopt stochastic frontier analysis to estimate farms' technical efficiencies.

Compared with the mean difference in technical efficiency between the SFMPs adopters and non-adopters, the positive and significant statistics of ATT reveal that farms with SFMPs are more efficient than traditional farms in vegetable production and productivity is increasing with the intensive adoption of SFMPs. Specifically, one-practice adopters would reduce efficiency in vegetable production by 0.06 if they had not adopted. Efficiency would shrink by 4.3% when switching from two-practice adoption to traditional production. The three-practice and four-practice adopters would have a score of 0.07 and 0.09 lower respectively if without any practice adoption. Overall, the findings emphasize the importance of the adoption of SFMPs among farmers as a means of improving soil fertility and farm productivity.

6. Conclusions and Implications

The results of this study show that: First, Of the 773 farms considered in the analysis, about 77.1% benefited from one or more SFMPs although all four SFMPs were applied in only 11 farms. Advanced irrigation is the most common SFMP used by the sample households and its adoption has a substitution effect with straw returning. Subsoiling practice is significantly correlated to straw returning and soil testing, suggesting that adoptions of SFMPs are interrelated.

Second, the probability and extent of adoption of SFMPs are influenced by several factors: householder educational level and cadre membership in the village are the important household characteristics variables that have high impacts on the adoption of SFMPs; The significant role of cooperative participation and training assistance in practice adoption suggests more accessible information enhance the adoption of SFMPs; farmers with higher social capital are more likely to adopt most practices; individual awareness and attitude to practice adoption play important roles in a household’s decision to adopt SFMPs.

Third, one-practice adopters would reduce efficiency in vegetable production by 0.06 if they had not adopted. Efficiency would shrink by 4.3% when switching from two-practice adoption to traditional production. The three-practice and four-practice adopters would have a score of 0.07 and 0.09 lower respectively if without any practice adoption. Overall, the findings emphasize the importance of the adoption of SFMPs among farmers as a means of improving soil fertility and farm productivity.

Several policy recommendations have emerged from the results of the Soil Fertility Management Study. Firstly, educational programs should be developed to disseminate information about SFMPs that is tailored to the needs of different farms and conducted by qualified agricultural experts. In addition, training should be provided to farmers on SFMPs and their benefits, and the exchange of knowledge and experience between farmers and other stakeholders, such as agricultural extension officers and agricultural researchers, should be facilitated. In addition, the formation of cooperatives should be encouraged and promoted to increase smallholder farmers' access to resources and markets, and support mechanisms should be put in place to ensure that cooperatives have access to the resources and services needed to effectively manage soil fertility. To further these objectives, the government should provide financial subsidies and incentives to smallholder farmers to encourage them to adopt tap water management schemes and to raise their awareness of sustainable agricultural production.

Reference:

Adolwa, I. S., Schwarze, S., & Buerkert, A. (2019). Impacts of integrated soil fertility management on yield and household income: The case of Tamale (Ghana) and Kakamega (Kenya). *Ecological Economics*, 161, 186-192.

Aryal, J. P., & Holden, S. T. (2012). Livestock and land share contracts in a Hindu society. *Agricultural Economics*, 43(5), 593-606.

Belderbos, R., Carree, M., & Lokshin, B. (2004). Cooperative R&D and firm performance. *Research policy*, 33(10), 1477-1492.

Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic surveys*, 21(1), 174-205.

Carter, D. W., & Milon, J. W. (2005). Price knowledge in household demand for utility services. *Land Economics*, 81(2), 265-283.

Chander, P., & Thangavelu, S. M. (2004). Technology adoption, education and immigration policy. *Journal of Development Economics*, 75(1), 79-94.

D'souza, G., Cyphers, D., & Phipps, T. (1993). Factors affecting the adoption of sustainable agricultural practices. *Agricultural and resource economics review*, 22(2), 159-165.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829-846.

Dorfman, J. H. (1996). Modeling multiple adoption decisions in a joint framework. *American Journal of Agricultural Economics*, 78(3), 547-557.

Dubin, J. A., & McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica: Journal of the Econometric Society*, 345-362.

Erenstein, O., & Farooq, U. (2009). Factors affecting the adoption of zero tillage wheat in the rice–wheat systems of India and Pakistan. *Outlook on Agriculture*, 38(4), 367-373.

Feder, G., & Umali, D. L. (1993). The adoption of agricultural innovations: a review. *Technological forecasting and social change*, 43(3-4), 215-239.

Frank Stephano, M., Geng, Y., Cao, G., Wang, L., Meng, W., & Meiling, Z. (2021). Effect of silicon fertilizer and straw return on the maize yield and phosphorus efficiency in Northeast China. *Communications in Soil Science and Plant Analysis*, 52(2), 116-127.

Geta, E., Bogale, A., Kassa, B., & Elias, E. (2013). Productivity and efficiency analysis of smallholder maize producers in Southern Ethiopia. *Journal of Human Ecology*, 41(1), 67-75.

Greene, W. H. (2008). The econometric approach to efficiency analysis. The measurement of productive efficiency and productivity growth, 1(1), 92-250.

Janvry, A. D., Fafchamps, M., & Sadoulet, E. (1991). Peasant household behaviour with missing markets: some paradoxes explained. *The economic journal*, 101(409), 1400-1417.

Kassam, A., Friedrich, T., Shaxson, F., & Pretty, J. (2009). The spread of conservation agriculture: justification, sustainability and uptake. *International journal of agricultural sustainability*, 7(4), 292-320.

Katengeza, S. P., Holden, S. T., & Fisher, M. (2019). Use of integrated soil fertility management technologies in Malawi: impact of dry spells exposure. *Ecological Economics*, 156, 134-152.

Martey, E., & Kuwornu, J. K. (2021). Perceptions of climate variability and soil fertility management choices among smallholder farmers in northern Ghana. *Ecological Economics*, 180, 106870.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

Ngango, J., & Seungjee, H. O. N. G. (2021). Adoption of small-scale irrigation technologies and its impact on land productivity: Evidence from Rwanda. *Journal of Integrative Agriculture*, 20(8), 2302-2312.

Pender, J. L., & Kerr, J. M. (1998). Determinants of farmers' indigenous soil and water conservation investments in semi‐arid India. *Agricultural Economics*, 19(1-2), 113-125.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of agricultural economics*, 64(3), 597-623.

Wollni, M., Lee, D. R., & Thies, J. E. (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural economics*, 41(3‐4), 373-384.

Figures

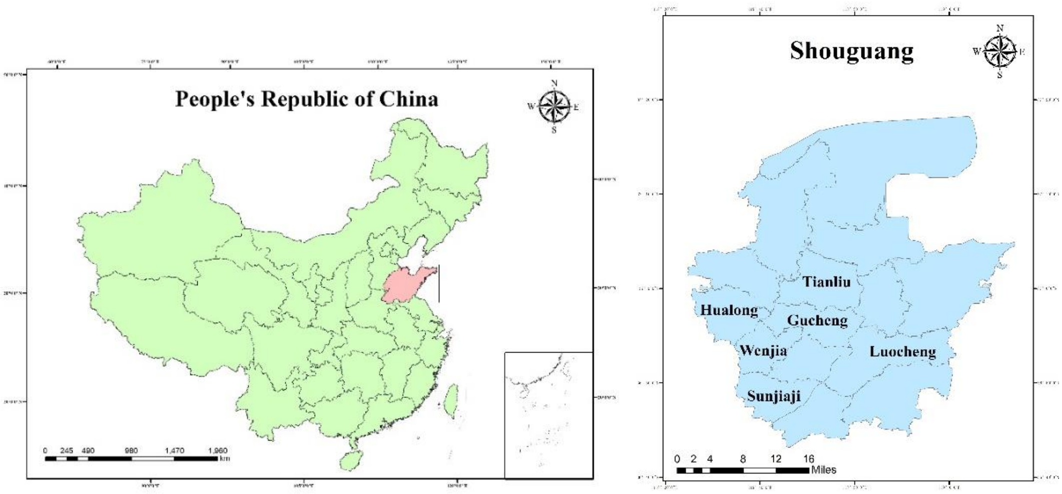

Figure 1 Map of the Study Area.

Source: Use ArcGIS Map to draw.

Tables

Table 1 Variable Selection and Descriptive Statistics

Variable	Interpretation	Mean (Standard deviation)				
		All (N=773)	Irrigation (N=426)	Straw return (N=83)	Subsoil (N=340)	Soil testing (N=140)
Independent Variables:						
Gender	Gender of household head: 1=Male; 0=Female	0.972	0.986	0.988	0.956	0.921
		(0.166)	(0.118)	(0.110)	(0.206)	(0.270)
Education	How many years of education does the household head have?	8.242	8.455	8.325	8.185	8.636
		(2.563)	(2.567)	(2.317)	(2.502)	(2.258)
Leader	Is a village leader or not? 1=Yes; 0=No	0.084	0.092	0.325	0.118	0.129
		(0.278)	(0.289)	(0.471)	(0.323)	(0.336)
Market	The distance from household to markets (mu)	1.974	2.157	2.406	1.830	1.952
		(3.213)	(3.938)	(5.541)	(2.215)	(1.640)
Off-farm	Have Off-farm incomes or not? 1=Yes; 0=No	0.591	0.622	0.711	0.553	0.700
		(0.492)	(0.485)	(0.456)	(0.498)	(0.460)
Ratio	Dependency ratio of those typically not in the labor force and those typically in the labor force	0.750	0.792	0.803	0.741	0.747
		(0.673)	(0.652)	(0.625)	(0.642)	(0.677)
Success	Satisfied with vegetable income or not? 1=Yes; 0=No	4.427	4.465	4.458	4.515	4.507
		(0.723)	(0.621)	(0.611)	(0.706)	(0.744)
Cooperative	Does the household participate in a cooperative? 1=Yes; 0=No	0.098	0.113	0.108	0.138	0.214
		(0.298)	(0.317)	(0.313)	(0.346)	(0.412)

Training	Is there training in the village?	1.582	1.547	1.458	1.524	1.343
		(0.494)	(0.498)	(0.501)	(0.500)	(0.476)
Internet	Access to an internet connection or not? 1=Yes; 0=No	0.216	0.244	0.434	0.259	0.329
		(0.412)	(0.430)	(0.499)	(0.439)	(0.471)
Peer	The extent that farmer is influenced by neighbors, friends, and relatives	3.646	3.730	4.012	3.918	3.864
		(1.063)	(0.948)	(1.110)	(0.965)	(0.883)
Ease of use	The extent that farmer values the ease of using practices	2.799	2.854	2.940	3.012	3.029
		(0.984)	(0.983)	(0.902)	(0.938)	(1.010)
Usefulness	The extent that farmer values the usefulness of practices	3.493	3.469	3.843	3.656	3.664
		(0.910)	(0.860)	(1.006)	(0.916)	(1.022)
Outcome Variable:						
Output	Vegetable sales revenue (yuan/mu)	40699.930	40732.720	42749.990	45187.760	42521.310
		(27584.040)	(22614.030)	(39867.510)	(32600.580)	(32398.250)
Input Variables:						
Fertilizer	The costs of fertilizers (yuan/mu)	6109.665	6235.153	4141.800	5571.209	5360.651
		(5315.396)	(5081.484)	(4085.442)	(4644.926)	(5090.002)
Pesticide	The costs of pesticides (yuan/mu)	1675.023	1617.642	991.762	1550.292	1801.769
		(2319.397)	(1708.271)	(1066.811)	(1969.934)	(1756.669)
Others	The costs of irrigation, seeds, plastic, and machinery (yuan/mu)	3570.636	4158.703	2430.842	3554.395	3898.005
		(4340.581)	(5399.642)	(3085.913)	(4564.214)	(6068.345)
Labor	Household labor costs (yuan/mu)	907.766	1058.828	837.822	1087.505	980.123
		(1832.800)	(1988.556)	(2857.631)	(2143.146)	(1728.770)
Land	The farm size of vegetables (mu)	3.966	4.786	7.397	4.427	4.976
		(5.301)	(6.419)	(12.100)	(6.519)	(8.096)

Source: Farm household survey (2019).

Notes: Numbers in the parentheses are the standard deviations; 1 mu ≈ 0.0667 hectares; 1 yuan = 0.141 US$ as per the exchange rates during the survey; Farm inputs and output in vegetable production are estimated on a per unit land basis.

Table 2 Marginal probabilities, unconditional and conditional probabilities of SFMPs adoption

Practice	Marginal probabilities	Unconditional and conditional probabilities			
		Irrigation	Straw	Subsoil	Soil testing
Irrigation	0.239	1	0.120	0.477	0.197
Straw	0.013	0.614	1	0.663	0.241
Subsoil	0.118	0.597	0.162	1	0.282
Soil testing	0.028	0.6	0.143	0.686	1
Irrigation, straw	0.022	1	1	0.667	0.216
Irrigation, subsoil	0.151	1	0.167	1	0.31
Irrigation, soil testing	0.027	1	0.131	0.75	1
Straw, subsoil	0.017	0.612	1	1	0.345
Straw, soil testing	0.001	0.55	1	0.95	1
Subsoil, soil testing	0.032	0.656	0.198	1	1
Irrigation, straw, subsoil	0.030	1	1	1	0.324
Irrigation, straw, soil testing	0.000	1	1	1	1
Irrigation, subsoil, soil testing	0.067	1	0.175	1	1
Straw, subsoil, soil testing	0.010	0.579	1	1	1
Irrigation, straw, subsoil, soil testing	0.014				
None adoption	0.229				

Source: Farm household survey.

Table 3 Correlations of SFMPs adoption

Practice	Irrigation	Straw	Subsoil	Soil testing
Irrigation	1	-0.141*	0.098	-0.022
		(0.077)	(0.060)	(0.076)
Straw	-0.141*	1	0.130*	-0.022
	(0.077)		(0.072)	(0.076)
Subsoil	0.098	0.130*	1	0.329***
	(0.060)	(0.072)		(0.065)
Soil testing	-0.022	-0.022	0.329***	1
	(0.076)	(0.076)	(0.065)	

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Farm household survey.

Table 4 Parameter estimates of multivariate regression model for SFMPs adoption

Variable	Straw	Irrigation	Plow	Soil testing
Gender	-0.143	0.874***	-0.645**	-1.096***
	(0.492)	(0.317)	(0.310)	(0.301)
Education	-0.018	0.054***	-0.009	0.047*
	(0.029)	(0.020)	(0.019)	(0.025)
Leader	1.032***	-0.238	0.418**	0.144
	(0.192)	(0.178)	(0.179)	(0.194)
Market	-0.023	0.013	-0.020	-0.006
	(0.021)	(0.020)	(0.016)	(0.018)
Off-farm	0.201	0.207*	-0.255**	0.285**
	(0.157)	(0.106)	(0.101)	(0.123)
Ratio	-0.024	0.020	-0.084	-0.042
	(0.112)	(0.078)	(0.076)	(0.090)
Success	-0.009	0.096	0.127*	0.031
	(0.109)	(0.070)	(0.068)	(0.081)
Cooperative	0.049	0.109	0.394**	0.760***
	(0.227)	(0.172)	(0.164)	(0.172)
Training	0.134	0.016	0.103	0.601***
	(0.154)	(0.106)	(0.101)	(0.121)
Internet	0.464***	0.097	-0.067	0.213
	(0.171)	(0.137)	(0.128)	(0.144)
Peer	0.120*	0.042	0.232***	0.046
	(0.071)	(0.048)	(0.047)	(0.059)
Ease of use	-0.109	0.086	0.142***	0.063
	(0.084)	(0.054)	(0.052)	(0.063)
Usefulness	0.225**	0.001	0.064	0.025
	(0.104)	(0.062)	(0.061)	(0.073)
Land	0.035***	0.046***	0.016	0.015
	(0.012)	(0.015)	(0.011)	(0.010)
Gucheng	-4.493	-0.159	-0.368*	0.036
	(182.650)	(0.208)	(0.216)	(0.286)
Hualong	0.912**	0.503***	-0.004	0.359
	(0.377)	(0.190)	(0.193)	(0.248)
Luocheng	0.998***	0.323	0.068	-0.062
	(0.385)	(0.201)	(0.206)	(0.281)
Sunji	0.622	1.132***	0.074	0.431*
	(0.383)	(0.195)	(0.191)	(0.247)
Tianliu	0.160	-0.782***	-0.139	0.517*
	(0.448)	(0.222)	(0.211)	(0.268)
Constant	-3.446***	-2.487***	-1.734***	-0.689
	(0.913)	(0.607)	(0.578)	(0.654)

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Farm household survey.

Table 5 Parameter estimates of ordered probit regression model for SFMPs adoption

Variable	Joint	Number of adopted practices				
		0	1	2	3	4
Gender	-0.297	0.076	0.017	-0.044	-0.042	-0.007
	(0.288)	(0.073)	(0.017)	(0.042)	(0.040)	(0.007)
Education	0.029**	-0.007*	-0.002*	0.004**	0.004*	0.001*
	(0.015)	(0.004)	(0.001)	(0.002)	(0.002)	(0.000)
Leader	0.496***	-0.126***	-0.029***	0.073***	0.070***	0.012**
	(0.162)	(0.041)	(0.010)	(0.023)	(0.023)	(0.005)
Market	-0.012	0.003	0.001	-0.002	-0.002	-0.000
	(0.009)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Land	0.038***	-0.010***	-0.002***	0.006***	0.005***	0.001***
	(0.010)	(0.003)	(0.001)	(0.002)	(0.001)	(0.000)
Off-farm	0.092	-0.023	-0.005	0.013	0.013	0.002
	(0.083)	(0.021)	(0.005)	(0.012)	(0.012)	(0.002)
Ratio	-0.049	0.012	0.003	-0.007	-0.007	-0.001
	(0.069)	(0.018)	(0.004)	(0.010)	(0.010)	(0.002)
Success	0.102	-0.026	-0.006	0.015	0.014	0.003
	(0.066)	(0.017)	(0.004)	(0.010)	(0.009)	(0.002)
Cooperative	0.458***	-0.117***	-0.027***	0.067***	0.064***	0.011***
	(0.127)	(0.033)	(0.008)	(0.019)	(0.019)	(0.004)
Training	0.247***	-0.063***	-0.014***	0.036***	0.035***	0.006**
	(0.083)	(0.021)	(0.005)	(0.012)	(0.012)	(0.003)
Internet	0.161	-0.041	-0.009	0.024	0.023	0.004
	(0.105)	(0.027)	(0.006)	(0.016)	(0.015)	(0.003)
Peer	0.172***	-0.044***	-0.010***	0.025***	0.024***	0.004***
	(0.040)	(0.010)	(0.003)	(0.006)	(0.006)	(0.002)
Ease of use	0.107***	-0.027***	-0.006**	0.016***	0.015**	0.003**
	(0.041)	(0.010)	(0.003)	(0.006)	(0.006)	(0.001)
Usefulness	0.106**	-0.027**	-0.006*	0.016**	0.015**	0.003*
	(0.053)	(0.013)	(0.003)	(0.008)	(0.007)	(0.001)
Gucheng	-0.290*	0.074*	0.017	-0.043*	-0.041*	-0.007
	(0.174)	(0.044)	(0.011)	(0.026)	(0.025)	(0.005)
Hualong	0.473***	-0.120***	-0.027***	0.069***	0.066***	0.012**
	(0.151)	(0.038)	(0.010)	(0.022)	(0.022)	(0.005)
Luocheng	0.342**	-0.087**	-0.020**	0.050**	0.048**	0.008*
	(0.158)	(0.040)	(0.010)	(0.023)	(0.023)	(0.004)
Sunji	0.744***	-0.189***	-0.043***	0.109***	0.105***	0.018***
	(0.149)	(0.038)	(0.011)	(0.021)	(0.023)	(0.006)
Tianliu	-0.264	0.067	0.015	-0.039	-0.037	-0.007
	(0.166)	(0.042)	(0.010)	(0.024)	(0.023)	(0.004)

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Farm household survey.

Table 6 Average treatment effects of technical efficiency for SFMPs adoption.

Number of practices	Non-adopter	Adopter	ATT
1	0.536	0.598	0.062***
	(0.087)	(0.052)	(0.089)
2	0.555	0.598	0.043***
	(0.085)	(0.071)	(0.069)
3	0.545	0.615	0.070***
	(0.116)	(0.069)	(0.101)
4	0.542	0.635	0.093
	(0.272)	(0.126)	(0.343)

Notes: Standard deviations in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Source: Farm household survey.