

Effects of the Adoption of Technology Combinations Beyond Standardized Systems on the Income of Chinese Tobacco Farmers

Yu Li¹, Yongjun Hua² & Zhiyong Zhu¹

¹ College of Economics and Management, Southwest University, Chongqing, China

² School of Economics and Business Administration, Chongqing University, Chongqing, China

Correspondence: Yongjun Hua, School of Economics and Business Administration, Chongqing University, Chongqing, 400044, China. Tel: 86-136-4767-7097. E-mail: huayongjun@cqu.edu.cn

Received: June 2, 2021

Accepted: June 29, 2021

Online Published: July 15, 2021

doi:10.5539/jas.v13n8p31

URL: <https://doi.org/10.5539/jas.v13n8p31>

The research is financed by the Fundamental Research Funds for the Central Universities (Project No. 2019 CDJSK 02 XK 06).

Abstract

Using the microdata for tobacco farmer households in Chongqing, China, this article analyses the determinants of adopting additional multiple agricultural technologies and their impact on income based on implementing a standardized technology system by a tobacco company. In this paper, selection bias from the observed and unobserved heterogeneity was corrected using a multinomial endogenous treatment effects model, and the endogenous properties were eliminated. The empirical results show that the adoption of a variety of additional agricultural technologies was determined by farmer's education level, years of tobacco planting, household size, number of technical training sessions, distance from farmer's family to the nearest tobacco technology extension station, distance from farmer's family to the nearest township, proportion of land suitable for machine farming, proportion of leased land. Different from empirical judgment, integrated pest management and balanced fertilization are the most effective additional technology combination strategies for increasing farmers' income instead of combining all additional comprehensive technologies. The research results suggest that Chongqing Tobacco Company should further strengthen the training of tobacco farmers and guide tobacco farmers to take appropriate pesticide and fertilizer input beyond the standardized technical system, especially for those tobacco farmers far away from the tobacco technology extension station.

Keywords: tobacco, income, technology, joint adoption, Chongqing, China

1. Introduction

In the process of agricultural production, farmers often face a series of technical choices that can be adopted individually or jointly (Feder, Just, & Zilberman, 1985; Mutale, Kalinda, & Kuntashula, 2017; Tesfaye, Blalock, & Tirivayi, 2020). Since Feder (1982) first developed a model to deal with interrelations in the adoption of multiple agricultural technologies (MATs), an increasing number of researchers have studied a variety of technology combination schemes (Cafer & Rikoon, 2018; Khanna, 2001; Kimbi et al., 2021; Wu & Babcock, 1998).

Most previous studies concluded that the more diversified the technology combination adopted by farmers, the better. The typical research evidence is that combining new varieties with complementary agronomic techniques and resource management practices can result in higher yields and income (Kassie et al., 2018; Tufa et al., 2019). Beaman, Karlan, Thuysbaert, and Udry (2013) found that with the increase in fertilizer use, female rice farmers in Mali optimized modern agricultural inputs, such as herbicides, obtaining a combined effect. Emerick, de Janvry, Sadoulet, and Dar (2016) conducted a randomized experiment in India. They found that a new rice variety and introducing other technologies (*e.g.*, fertilizer and labor-intensive cropping methods) can increase income through factor deepening effects, downside risk effects, and wealth effects. Kassie et al. (2018) found that farmers in Ethiopia who adopted improved maize seeds, chemical fertilizers and legume diversification generated the highest payoffs. Khonje, Manda, Mkandawire, Tufa, and Alene (2018) showed that compared to farmers who adopted one measure alone, farmers in eastern Zambia who adopted Climate-smart agriculture (CSA) interventions using both conservation agricultural practices (CAPs) and improved maize varieties (IMVs) obtained maximum yields and

household income. Martey, Etwire, Mastenbroek, and Abdoulaye (2020) found that farmers in Ghana increased their income by adopting a combination of two CSA technologies: row planting and drought-tolerant maize seeds. In a study of Kenyan mango farmers, Midingoyi, Kassie, Muriithi, Diiro, and Ekese (2019) highlighted that transitioning from one type of integrated pest management (IPM) to multiple IPM practices generated more economical, environmental and human health benefits. Tambo and Mockshell (2018) showed that the joint adoption of three components of conservation agriculture (CA) by farmers in Sub-Saharan Africa (SSA) had the greatest benefits. Teklewold, Kassie, Shiferaw, and Köhlin (2013) found that Ethiopian farmers who adopted a combination of three sustainable agricultural practices (SAPs), *i.e.*, cultivation system diversification, conservation tillage and modern maize seeds, generated the highest income. A study by Zeweld, Van Huylenbroeck, Tesfay, Azadi, and Speelman (2020) in Ethiopia indicated that the combination of three sustainable development technologies (contour terracing or water and soil conservation, animal manure and crop residues) resulted in the highest per capita income.

However, some scholars have proposed different opinions, suggesting that technology combination schemes that are more diverse are not always better. Adolwa, Schwarze, and Buerkert (2019) found that farmers in northern Ghana and western Kenya adopted integrated soil fertility management (ISFM) to increase maize production. However, increasing the number of ISFM components did not improve maize yield or total household income. Ainembabazi et al. (2018) reported that farmers in Central Africa who adopted either one technical package or a combination of two technical packages (but not all), *i.e.*, AR4D technologies (improved crop varieties (IVs)), crops and natural resource management (CNRM), and post-harvest (PH) technology, gained much greater benefits related to reducing poverty than those who adopted all technologies simultaneously. Di Falco and Veronesi (2013) found that in the Nile basin of Ethiopia, farmers who simultaneously adopted three climate change adaptation strategies, including water conservation strategies, soil conservation strategies, and crop rotation, did not generate a higher net income than those who adopted two strategies. Manda, Alene, Gardebroek, Kassie, and Tembo (2016) found that the combined use of SAPs in Zambia was more favorable to increasing income than SAPs alone. However, the per capita income was not the highest with the simultaneous adoption of three SAPs. Mutenje, Kankwamba, Mangisonib, and Kassie (2016) found that farmers in Malawi who adopted three technologies, *i.e.*, improved maize, soil and water conservation, and improved storage, simultaneously increased per hectare maize yield by 10% compared to 14% for those who adopted improved maize alone and 29% for those who adopted improved storage and improved maize.

The different conclusions of the above studies indicate that different technologies are not mutually independent (Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Teklewold et al., 2013) and that a complementary, substitute or supplementary function is commonly present between technologies in technical combination schemes (Kassie, Teklewold, Jaleta, Marennya, & Erenstein, 2015a). Amadu, McNamara, and Miller (2020), and Kassie, Teklewold, Marennya, Jaleta, and Erenstein (2015b) also showed that synergies among technical combinations could promote income growth. Zeweld et al. (2020) reported that the combination of animal manure and retained crop residue resulted in a negative yield effect, likely due to the substitution effect between the two and simultaneous use resulting in a decrease in yield.

Existing studies mainly focused on rice, maize and wheat (Mishra, Khanal, & Pede, 2017; Mastenbroek, Sirutyte, & Sparrow, 2021; Abate, Bernard, Brauw, & Minot, 2018). This study takes tobacco as the research object. Tobacco is an important economic crop in developing countries and is generally produced based on contracts (including in China) (Appau, Drope, Witoelar, Chavez, & Lencucha, 2019; Appau et al., 2020; Briones, 2015; Magati, Lencucha, Li, Drope, & Zulu, 2019; Makoka et al., 2017; Scoones, Mavedzenge, Murimbarimba, & Sukume, 2018). Every year, Chongqing Tobacco Company (CTC) develops a set of standardized technical systems as a compulsory production standard. Based on our long-term field observations, and due to land heterogeneity and complex climate changes, tobacco farmers commonly adopt MATs in addition to strictly implementing standardized technical systems to maximize their income. These additional technologies mainly include IPM, balanced fertilization (BF), and soil improvement (SI). This paper is different from previous studies. First, we focus on tobacco as a special agricultural product. It also significantly contributes to households' income in the study area. The Framework Convention on Tobacco Control (FCTC) advocated a gradual reduction in tobacco supplies worldwide. China has a national tobacco monopoly with a strict quota management system. There are very few studies on the adoption of tobacco technology. Dimara and skuras (1998) studied the adoption of a new flue-cured tobacco variety in Greece. Omara, Odongo, and Kule (2021) assessed tobacco farmers' perception and factors affecting the adoption of rocket barn technology in Uganda. Second, this paper studies the income effect of multiple technical combinations beyond the scope of standardized technology systems. Previous studies have mainly focused on standardized technologies without considering land heterogeneity and the individuality of the

farmers. Third, this study considers the quality of heterogeneity of tobacco. Previous studies generally assumed that agricultural products were homogenous and seldom took into account that prices increased as the quality grade increased. Before the production season, the China National Tobacco Company (CNTC) releases price rankings for 40 grades of tobacco. The prices of different quality grades vary greatly, significantly affecting the income of tobacco farmers. The findings of this study will contribute to help tobacco farmers achieve income growth within the limits of the tobacco production quota for the FCTC.

2. Tobacco-Planting Technology in Chongqing

Tobacco is an important economic crop in China, and tobacco planting area and yields rank first in the world. Chongqing's tobacco planting distribution encompasses 12 districts and counties in the Three Gorges Reservoir Area and the Wuling Mountainous Area, which lies one of the major tobacco-producing region in China. The average elevation of the area is about 800-1400 m, typical for tobacco-growing regions in the mountains. Tobacco is one of the few economic crops in the areas due to the natural environmental factors which are similar to tobacco-producing areas in Indonesia and the Philippines (Appau et al., 2019). In 2018, approximately 405,700 mu (1 mu = 1/15 hectares) of tobacco were planted, and 46.7 million kg of flue-cured tobacco were produced.

At the beginning of each year, CTC publishes the purchase price per unit of each grade of tobacco and, at the same time, signs cultivation contracts with tobacco farmers, agreeing on planting area, unit yield and total output based on the production quota. CTC sets up tobacco technology extension stations in various planting areas so that tobacco technicians can train, guide and supervise tobacco planting following the standardized technical system. Additionally, they organize tobacco farmers into cooperatives (farmers are all members of cooperatives) and help solve technological difficulties in the planting process.

In December 2008, CTC applied the ISO9000 quality standard management system for tobacco planting. Each year, a technical programme for planting under normal weather conditions is developed in advance to provide a standardized technical system, as mandatory production specifications cover the entire tobacco planting process. CTC provides a unified and specialized service for some processes that are labor intensive and have high technical requirements, such as raising seedlings, mechanized farming, plant protection, flue-curing, and grading. Each household performs transplanting, uncovering, weeding, topping and pruning, and picking separately. Due to differences in climate, elevation, and vegetation and differences in soil thickness, fertility, and slope in tobacco-growing areas, tobacco farmers generally adopt multiple additional agricultural technologies. Chongqing tobacco farmers usually adopt three main additional technologies: IPM, BF and SI.

3. Methodology

The present study is based on diffusion of innovations theory (Rogers, 2003) and induced innovation theory (Binswanger & Ruttan, 1978; Ruttan & Hayami, 1984). The diffusion of innovations theory held that the characteristics of innovation, such as comparative advantage and testability, would determine its adoption rate. Farmers usually consider the potential benefits, which include increased production, reduced cost, enhanced efficiency and so on, when deciding on new technologies. The induced innovation theory emphasized that farmers were influenced and induced by the change of factor price, and would strive to adopt the technology that can replace the scarce resources, thus the relative abundance of resource endowment would affect the adoption of technology, such as labor and capital. Adoption decisions on agricultural technology depend on the individual optimization of expected utility or earnings (Feder et al., 1985). Michler, Tjernström, Verkaart, and Mausch (2019) argued that relative to yield targets, farmers focus more on economic return indicators when making decisions. Based on Khonje et al. (2018) and Tesfaye et al. (2020), this study used a random utility framework to analyse the adoption of multiple additional agricultural technologies, including IPM, BF, and SI, in a total of seven possible combinations: (i) IPM only, (ii) BF only, (iii) SI only, (iv) IPM & BF, (v) IPM & SI, (vi) BF & SI, and (vii) IPM & BF & SI. It is assumed that tobacco farmers aim to maximize their utility by comparing various combinations of technology combination options. Therefore, if $V_{ij} > V_{ik}$, $k \neq j$, tobacco farmer i selects technology combination j instead of any other combination k .

When making decisions regarding adopting technology, tobacco farmers are affected by many factors, including observable and unobservable factors, which may lead to endogeneity problems. For example, tobacco farmers may decide to adopt a technology combination scheme based on their innate management and technical capabilities related to understanding and using technology (Abdulai & Huffman, 2014). If we do not consider unobservable factors, the real impact of MATs may be overestimated or underestimated.

With the empirical approach of Manda et al. (2016) as a reference, a multinomial endogenous treatment effects model (Deb & Trivedi, 2006b) is used herein to explain the selection bias due to the observed and unobserved heterogeneity and to evaluate the differential effects of multiple agricultural technology combinations. When

assessing adoption decisions, the multinomial endogenous treatment effects model allows the modelling of interdependence among different technologies. Compared with the multinomial endogenous switching regression (MESR) method adopted by many researchers (Di Falco & Veronesi, 2013; Martey et al., 2020), the multinomial endogenous treatment effects model is easier to implement and allows the distribution of endogenous treatments (adoption of MATs) and output outcomes (such as yield and income) to be specified using a latent factor structure, thereby distinguishing unobservable and observable choices (Deb & Trivedi, 2006b). The multinomial endogenous treatment effects model improves the estimation effect by reducing the endogenous impact.

This model not only considers the interdependence of adoption decisions but also considers selection bias due to observed and unobserved characteristics. In the first stage, a mixed multinomial logit selection model was used to model adoption decisions. In the second stage, ordinary least squares (OLS) and selectivity correction were used to estimate the effects of the adoption of additional MATs on yield per mu (YPM), the average sales price of tobacco (ASPT), and income per household labor engaged in tobacco planting (IPHL). It is hereby noted that ASPT is equal to total tobacco revenue by total output, which reflects the level of tobacco quality grade.

3.1 Multinomial Endogenous Treatment Effects Model

The multinomial endogenous treatment effects model has two stages. In the first stage, the tobacco farmers selected one of the above seven MAT combinations. Based on Deb and Trivedi (2006a, 2006b), V_{ij}^* indicates the indirect utility associated with the j th MAT combination, $j = 0, 1, 2, \dots$, and i represents tobacco farmers:

$$V_{ij}^* = z_i' \alpha_j + \sum_{k=1}^J \delta_{jk} l_{ik} + n_{ij} \quad (1)$$

where, z_i is the vector of the covariates, such as characteristics of tobacco farmers and plot features discussed in Section 3.3; α_j is the vector of the corresponding parameter to be estimated; n_{ij} is an independent and identically distributed error term; and l_{ik} is a latent factor that includes the unobserved farmer and tobacco field characteristics shared by the tobacco farmers in the adoption of MATs and their output outcomes as well as the influence of observable factors that may be associated with the outcome variables (Abdulai & Huffman, 2014; Pannell, Llewellyn, & Corbeels, 2014). In the above equation, $j = 0$ means non-adopter, and at this point, $V_{i0}^* = 0$. Although V_{ij}^* is not observed, the choice of MAT combinations is a set of binary variables d_j . The set of these variables can be expressed as vectors $d_i = d_{i1}, d_{i2}, \dots, d_{iJ}$. Similarly, let $l_i = l_{i1}, l_{i2}, \dots, l_{iJ}$; then, the probability of processing can be written as follows:

$$\Pr(d_i | z_i, l_i) = g \left(z_i' \alpha_1 + \sum_{k=1}^J \delta_{1k} l_{ik} + z_i' \alpha_2 + \sum_{k=1}^J \delta_{2k} l_{ik} + \dots + z_i' \alpha_J + \sum_{k=1}^J \delta_{Jk} l_{ik} \right) \quad (2)$$

where, g is the appropriate distribution of multinomial probability. If g has a mixed multinomial logit (MMNL) structure, g is defined as follows:

$$\Pr(d_i | z_i, l_i) = \frac{\exp(z_i' \alpha_j + \delta_j l_{ij})}{1 + \sum_{k=1}^J \exp(z_i' \alpha_k + \delta_k l_{ik})} \quad (3)$$

In the second stage, we assessed the effect of adopting the MAT combinations on the three outcome variables, namely, the natural logarithms of YPM, ASPT, and IPHL. The formula is as follows:

$$E(y_i | d_i, x_i, l_i) = x_i' \beta + \sum_{j=1}^J r_j d_{ij} + \sum_{j=1}^J \lambda_j l_{ij} \quad (4)$$

In this equation, y_i is the output outcomes of tobacco farmer i , x_i represents the exogenous covariate for parameter vector β , and parameter r_j represents the effect of MATs on the output outcome of tobacco farmers. The variable d_{ij} is the coefficient parameter of r_j ; if d_{ij} is assumed to be exogenous and the decision to adopt MATs is endogenous, the estimation of r_j would be inconsistent. The latent factor is l_{ij} , indicating that the unobserved characteristic variables can affect not only the output outcomes but also the selection of technology combination schemes. The load factor λ_j represents the direction of the correlation between the treatment effect and the outcome variable. When λ_j is positive (negative), the treatment effect and outcome variable are positively (negatively) related through unobserved characteristics, *i.e.*, positive (negative) choice exists. Because the outcome variables are continuous, it is assumed that they follow a normal (Gaussian) distribution function. We estimated the model using the maximum simulated likelihood (MSL) method.

The instrumental variable approach is generally adopted to solve the endogeneity of technology adoption decisions (Suri, 2011). The selected instrumental variables will impact the adoption of technological schemes but will not directly affect the output outcomes (such as yield and income) except through the adopted decisions. Based on Gao, Niu, Yang, and Yu (2019), Manda et al. (2016), and Khonje et al. (2018), the instrumental variables selected in this paper included the distance from farmer family to tobacco technology extension stations (This variable reflects

how convenient it is for tobacco farmers to obtain technical information and technical guidance from tobacco technicians), the proportion of flat land area (the ratio of land suitable for mechanized farming to the total tobacco farmland), and the proportion of leasehold land (the ratio of leasehold land to the total tobacco farmland). We show that these three instrumental variables are effective through a simple falsification test and that they jointly affect MATs adoption decisions (test results in Table 3) but do not affect the output outcome variables (test results in Table A3).

3.2 Data Collection

Cross-sectional survey data for tobacco farmers in Chongqing were used in this study. The survey was conducted in all 12 tobacco-planting districts/counties in Chongqing from March to June 2019, and a total of 500 questionnaires were used to collect data. The sample size for the questionnaire survey in each district/county was determined based on the tobacco production quota, and trained professionals randomly selected tobacco farming villages to conduct household surveys, distribution of questionnaires is shown Table A1. Before the official start of the survey, a pre-survey was conducted in Qianjiang District, one of the main production areas, in February of the same year to supplement and improve the questionnaire design and investigation process.

The questionnaire collected comprehensive information on heads of household and families, knowledge of tobacco-planting technology, and technology adoption in 2018, specifically including the adoption level of the standardized technology system promoted by CTC and the adoption of additional technologies, *i.e.*, IPM, BF, and SI. We also obtained the actual data for tobacco farmers' acquisition information for 2018 through the Chongqing Tobacco Science Research Institute; these data included sales volume, quality grade, average sales price, and sales revenue for each tobacco farmer.

We defined the additional three technologies as binary variables. If the farmers chose to purchase and use pesticides on at least one plot following the list of pesticides recommended by CTC, then IPM took a value of 1; otherwise, it took a value of 0. If the farmers chose to purchase and use fertilizers on at least one plot in accordance with the list of fertilizers recommended by CTC, then BF was set to 1; otherwise, it was set to 0. SI was set as 1 if the tobacco farmer used measures such as deep ploughing, green manure planting and tilling, and the application of dolomite powder, oyster shell powder or lime to adjust the pH value on at least one plot; otherwise, it was set to 0.

This paper adopted a similar strategy as Suri (2011). It did not include household labor in tobacco farming costs, and the return function was approximated with a total income function for technology adoption. Therefore, the survey did not collect specific data on the planting costs of tobacco farmers.

A total of 384 valid questionnaires were finalized, for an effective rate of 76.80%. The low effective rate was a result of matching the information from the questionnaire with tobacco farmers' acquisition information one by one and excluding the missing data and tobacco farmers who did not grow tobacco in 2018 to ensure objective and realistic results.

3.3 Description of the Variables

Based on theoretical analyses and combing the previous literature (Di Falco, Bezabih, & Yesuf, 2010; Feder et al., 1985; Lee, 2005), this study used indicators such as head of household characteristics (gender, age, education level, and years of tobacco farming), household characteristics (family size and tobacco farming labor), and plot characteristics (tobacco farming area); furthermore, the following variables related to the actual situation of tobacco farmers in Chongqing were considered.

Labor force ratio: This variable reflects the ratio of the labor force (16-65 years old) to total family size.

Number of training sessions: Taking into account that tobacco farmers have regular access to technical training from CTC and technical guidance from tobacco technicians, the number of times that tobacco farmers participated in agricultural technology training in a year was selected to reflect farmers' knowledge and mastery of various planting technologies.

Loan: Farmers can easily obtain credit support from banks with a tobacco company's planting contract. Most tobacco farmers' households generally have good cash flow income, and their own funds can guarantee planting needs. Therefore, the collected information only reflects whether the farmers have taken a loan from a bank.

Distance to the nearest township: The distance to the nearest township reflects the transaction costs of planting inputs, hiring workers, and the availability of new technology, information and credit institutions (Kassie et al., 2013).

4. Results and Discussion

4.1 Descriptive Statistics

Table 1 provides the descriptive statistics of relevant variables. Considering that only one sample did not adopt any of the three technologies, this sample was excluded, and 383 samples were used for the empirical analysis. On this basis, we generated new combinations whose distribution is shown in Table 2.

Table 1. Descriptive statistics of the variables

Variables	Description	Mean	SD
<i>Outcome variables</i>			
YPM	Yield per mu (kg/mu)	114.01	30.06
ASPT	Average sales price (Yuan ^a /kg)	27.77	2.13
IPHL	Income per household labour engaged in tobacco planting (ten thousand RMB)	6.00	3.96
<i>Treatment variables</i>			
IPM	Adopt IPM technology in at least one plot (1 = yes)	0.79	0.41
BF	Adopt BF technology in at least one plot (1 = yes)	0.95	0.22
SI	Adopt SI technology in at least one plot (1 = yes)	0.87	0.33
<i>Explanatory variables</i>			
Age	Age of the head of household (years)	49.97	7.10
Gender	Gender of the head of household (1 = male)	0.93	0.25
Education ^b	Formal education experience of the head of household	2.65	0.73
Planting years	Years of tobacco farming (year)	20.55	9.93
Household size	Family size (number of people)	4.89	1.43
Social capital	Village cadre in the family (1 = Yes)	0.15	0.36
Planter	Tobacco farming labour (number of people)	2.08	0.63
Area	Area of tobacco farming (mu)	38.16	22.73
Distance1	Distance to the nearest township (km)	8.59	7.08
Loan	Loan (1 = Yes)	0.43	0.50
Train	Number of technical training sessions during the year	5.20	2.51
Labour force ratio	Ratio of labour force (16-65 years old) to total family size	0.69	0.23
<i>Instrumental variables</i>			
Distance2	Distance to the nearest tobacco technology extension station (km)	5.22	4.81
Flatland	Proportion of land suitable for machine farming to area of total tobacco farmland	0.72	0.30
Leaseland	Proportion of leasehold land to the area of total tobacco farmland	0.67	0.51
Number of obs.		384	

Note. ^a Yuan is the Chinese currency: 1 USD = 6.62 Yuan in 2018. ^b 1, 2, 3, 4, and 5 indicate never attended school, elementary school, junior high school, high school (secondary), or junior college or above, respectively.

Table 2. Proportion of tobacco farmers who adopted different technical combinations

	IPM only	BF only	IPM & BF	SI only	IPM & SI	BF & SI	IPM & BF & SI	Total
Freq.	4	4	40	6	8	70	251	383
Percent	1.04	1.04	10.44	1.57	2.09	18.28	65.54	100.00

Note. From the sample structure analysis, the sample sizes for IPM only, BF only, SI only and IPM & SI are small and not representative. Therefore, this paper focuses on three combinations: IPM & BF, BF & SI, and IPM & BF & SI. The descriptive statistics of these technology combinations are shown in Table A2.

Table 3. Estimate of the mixed multinomial logit model using MATs in Chongqing, China (baseline category is the adoption of the additional three MATs)

Variables	IPM only	BF only	IPM & BF	SI only	IPM & SI	BF & SI
Age	-0.0804 (0.115)	0.0571 (0.0953)	0.0277 (0.0282)	0.0446 (0.0807)	0.0273 (0.0600)	0.00461 (0.0252)
Education	-0.788 (1.180)	0.603 (1.158)	0.000408 (0.259)	-1.939** (0.852)	-0.231 (0.630)	-0.623** (0.247)
Years	0.0315 (0.0777)	-0.175* (0.101)	-0.00485 (0.0202)	-0.0471 (0.0582)	0.0374 (0.0514)	-0.0799*** (0.0187)
Homesize	-1.630* (0.844)	2.072* (1.156)	0.272* (0.153)	0.102 (0.408)	-0.291 (0.304)	-0.0349 (0.149)
Planter	1.575 (1.082)	0.0201 (0.936)	0.217 (0.280)	0.274 (0.945)	-0.641 (0.831)	0.286 (0.258)
Area	0.0179 (0.0256)	0.00839 (0.0487)	0.0197** (0.00841)	0.0408* (0.0225)	0.00920 (0.0255)	0.0236*** (0.00808)
Distance1	-0.124 (0.126)	0.213* (0.109)	0.0681*** (0.0241)	-0.109 (0.135)	-0.0724 (0.0812)	-0.0541 (0.0337)
Loan	-0.185 (1.369)	-0.635 (1.777)	-0.339 (0.393)	0.0154 (1.062)	-0.779 (0.995)	-0.442 (0.355)
Train	-0.0163 (0.220)	0.0921 (0.455)	0.105 (0.0724)	0.358* (0.198)	-0.351* (0.200)	0.230*** (0.0664)
Labour	-3.503 (2.181)	14.54 (9.533)	0.192 (0.981)	-2.048 (2.539)	-2.680* (1.628)	-0.114 (0.868)
<i>Instrumental variable</i>						
Distance2	0.119 (0.120)	-0.229 (0.298)	-0.0608 (0.0398)	-0.398* (0.218)	-0.217 (0.180)	-0.261*** (0.0611)
Flatland	-3.922* (2.261)	1.728 (4.167)	-1.111* (0.609)	-2.132 (1.791)	-2.034 (1.266)	-1.761*** (0.568)
Leaseland	0.171 (1.305)	-6.953** (3.326)	-0.314 (0.638)	0.283 (0.689)	0.339 (0.492)	-2.129*** (0.547)
Constant	8.653 (8.820)	-28.89** (14.55)	-5.628*** (2.022)	-0.803 (6.183)	3.285 (4.312)	3.288* (1.943)
Joint significance of instrumental variables $\chi^2(18) = 47.87^{***}$						
Wald test $\chi^2 = 114.97$; $P > \chi^2 = 0.0041$						

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses.

4.2 Determinants of MATs Adoption

It was noted that 78.91% of tobacco farmers adopted IPM, 95.05% adopted BF, and 87.24% adopted SI, while more than 65% of tobacco farmers adopted a combination of the three types of technology. Considering the nature of the logit model, we used adoption of the three additional technologies as the baseline. This approach is different from those taken by Manda et al. (2016) and Khonje et al. (2018), who took non-adopters as the baseline. Table 3 shows the parameter estimation of the MMNL model, which is equivalent to the first stage of the multinomial endogenous treatment effects model. The fitting degree of this model, based on the Wald test, was very good ($\chi^2 = 114.97$, $P > \chi^2 = 0.0041$), indicating that the null hypothesis was rejected.

As mentioned above, the adoption of the additional three technologies was used as the baseline in this study, and the subsequent comparative analysis was based on it.

The results show that the adoption of IPM & BF was positively affected by household size, tobacco farming area, and distance to the township and negatively affected by the proportion of flat land. That is, the larger the household size and tobacco farming area, the more farmers are inclined to adopt the inputs of pesticides and fertilizers. The regression results were significant in terms of the distance to the township, indicating that the farther the distance from the township, the more tobacco farmers tended to adopt IPM & BF, showing that influenced by Chinese planting experience and culture, the farther away from the township, the more tobacco farmers tend to increase investments in pesticides and fertilizers to improve their inner sense of security

The adoption of BF & SI was significantly positively affected by the tobacco farming area and the number of training sessions. It was significantly negatively impacted by education level, years of tobacco farming, distance to a tobacco technology extension station, proportion of flat land, and proportion of leasehold land. The results indicate that tobacco farmers with more area for tobacco farming and more training tended to choose the BF & SI combination. Furthermore, the results indicate that the higher the education level, the higher the tendency of tobacco farmers to adopt IPM & BF & SI than BF & SI. In terms of years of tobacco farming, with increasing years of farming, tobacco farmers were more willing to adopt IPM & BF & SI rather than BF & SI. This finding may be due to a greater belief in the combined application of multiple technologies as years of farming increases. In terms of distance to a tobacco technology extension station, the greater the distance, the more tobacco farmers preferred to adopt IPM & BF & SI, which may be due to a greater distance leading to greater psychological dependence of tobacco farmers on the diversity of technology combinations. In terms of the proportion of leasehold land, tobacco farmers tended to adopt IPM & BF & SI as the proportion of leasehold land increased.

The greater the proportion of flat land, the more tobacco farmers preferred to adopt IPM & BF & SI rather than BF & SI or IPM & BF. It is possible that the greater the proportion of flat land, the easier it is for tobacco farmers to

implement multiple agricultural technologies, which can reduce labor intensity and improve operational efficiency.

In the empirical study, the regression results for age of head of household were non-significant, a finding similar to that in a study of the adoption of CA technologies by Tambo and Mockshell (2018). Our analysis suggested that the possible reason was the low education level of tobacco farmers and a lack of independent knowledge concerning various types of agricultural production technologies, leading to a herd mentality in the adoption of additional agricultural technologies.

Based on the literature related to technology adoption in developing countries, such as those in Africa, credit is an important support mechanism related to technology adoption (Cafer & Rikoon, 2018), but the empirical results in this study showed the variability of loans for farmers is not significant; on the one hand, tobacco farmers may have sufficient funds and thus can generally afford extra technologies, and on the other hand, even if the farmers do not have enough funds, they can easily obtain a special bank loan by virtue of their planting contracts with CTC. These results indicate that funding is not a constraint to technology adoption.

The regression results for the number of household members engaged in tobacco farming were also not significant, which may be due to two reasons. First, CTC promotes adjustments to production organization modes, which deepens the agricultural division of labor, and provides specialized services (access to service economies of scale) in multiple production processes (such as raising seedlings, mechanized farming, plant protection, flue-curing, and grading). Second, it is common for tobacco farming families to hire workers during the busy farming season, making it possible to achieve larger scale planting with a smaller amount of tobacco farming labor.

Notably, in the regression model, the variables of the gender of the head of household and social capital were removed. Based on actual practices, the tobacco technical services provided by CTC to tobacco farmers are universal, and there are no differences in gender or social status.

4.3 Average Treatment Effect of MATs

Table 4 provides the estimated results for the effects of the adoption of additional MATs on YPM, ASPT and IPHL. The results of two normal regressions (second stage) are provided in Table A4 (the regression results for the mixed multinomial treatment effects are not shown to conserve space but are available upon request). For comparison, the regression results were estimated under the assumptions of exogenous and endogenous adoption decision of MATs with the adoption of the three additional technologies as the baseline.

Table 4. Estimation of the multinomial endogenous treatment effects model for the effect of MATs on YPM, ASPT and IPHL in Chongqing

Assumptions	Package	Ln YPM	Ln ASPT	Ln IPHL
Exogenous	IPM only	-0.0566 (0.111)	0.0329 (0.0282)	0.112 (0.148)
	BF only	0.0848*** (0.0317)	-0.0274* (0.0141)	0.0857* (0.0513)
	IPM & BF	0.127 (0.162)	0.0228 (0.0314)	0.171* (0.0990)
	SI only	0.246 (0.154)	0.00532 (0.0573)	0.212 (0.151)
	IPM & SI	-0.00416 (0.0335)	0.0243*** (0.00933)	-0.0159 (0.0447)
	BF & SI	0.104** (0.0414)	0.0381** (0.0173)	0.142* (0.0730)
Endogenous	IPM only	-0.125 (0.129)	0.0465*** (0.00828)	0.268*** (0.0399)
	BF only	0.0770 (0.0501)	-0.0373*** (0.00214)	0.194*** (0.0146)
	IPM & BF	0.205** (0.101)	0.0882*** (0.00343)	0.269*** (0.0263)
	SI only	0.205 (0.125)	0.0157*** (0.00395)	0.170*** (0.0534)
	IPM & SI	-0.0527 (0.0428)	0.00497*** (0.00188)	-0.0708*** (0.0159)
	BF & SI	0.118 (0.108)	0.0750*** (0.00777)	0.248*** (0.0259)
Selection terms(λ)	IPM only	0.0852** (0.0373)	0.0355*** (0.000746)	-0.162*** (0.00499)
	BF only	0.0132 (0.0301)	-0.00978*** (0.000813)	-0.0000220 (0.00456)
	IPM & BF	-0.0940** (0.0441)	-0.0323*** (0.000650)	-0.0199*** (0.00565)
	SI only	0.0563 (0.0344)	0.0428*** (0.000673)	0.231*** (0.00334)
	IPM & SI	0.0723** (0.0333)	0.0389*** (0.000723)	0.130*** (0.00453)
	BF & SI	-0.0125 (0.0332)	-0.0271*** (0.000718)	-0.0707*** (0.00509)

Note. *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses.

The results showed that for adopting the exogenous model of MATs, on average, BF & SI had significant effects on YPM, ASPT and IPHL, while IPM & BF only had a significant impact on IPHL. Compared with adopting all three technologies, the application of BF & SI increased YPM and increased ASPT. Both of them led to an increase in the IPHL (Table 4). However, IPM & BF was only conducive to improving IPHL. The above results are statistical inferences based on the observed characteristics without considering the unobserved influencing factors. Thus, there were endogeneity problems, and the results may be biased. To solve this problem and take into account some of the influencing factors that are not observed, we used a multinomial endogenous treatment effects model.

After the treatment for endogeneity, the average adoption effect when controlling for unobserved heterogeneity showed a difference (Table 4), and the validity of estimation was significantly improved. BF & SI had a significant positive impact on ASPT and IPHL. IPM and BF had a significant positive impact on YPM, ASPT, and IPHL. In terms of value, compared with the adoption of all three technologies, the adoption of BF & SI resulted in an average increase of 7.50% in ASPT and an average increase of 24.80% in IPHL. The adoption of IPM & BF resulted in an average increase of 20.50% in YPM, an average increase of 8.82% in ASPT, and an average increase of 26.90% in IPHL. The combined effects of yield and quality-enhancement led to an increase in IPHL. Notably, although the adoption of IPM & BF significantly increased yield, CTC only purchased the contracted output, and the excess was innocuously disposed of by tobacco farmers. Therefore, the income effect reflected the actual increase in tobacco farmers' income. Compared with the result under the exogenous hypothesis, the estimated value after considering unobservable characteristics was relatively higher, indicating that the actual effect of adoption will be underestimated without consideration of endogeneity.

As seen in Table 4, with the adoption of all three additional technologies as the baseline, the adoption factor load (λ) of BF & SI in the sales price equation and the income equation exhibits negative selection bias, and the factors load (λ) of the yield equation, the sales price equation and the income equation for IPM & BF all show negative selection biases. These results indicated that although the unobservable factors improved the possibility of adopting BF & SI, they had a lower impact on ASPT and IPHL. Unobservable factors can improve the possibility of adopting IPM & BF, while they had a lower impact on YPM, ASPT and IPHL.

Finally, OLS approach is also implemented as a means of robustness checks, results are shown in Table A5. On the whole, the robustness check reveal that the treatments effects discussed above are robust.

5. Conclusions and Implications

5.1 Conclusions

The present study found heterogeneity in factors affecting the adoption of additional different combinations of MATs by tobacco farmers. Specifically, the higher the education level of tobacco farmers, the more years of tobacco farming, the farther the families are from tobacco technology extension stations, and the higher the proportion of flat land and the proportion of leasehold land, the more farmers tend to adopt three additional technology combinations, *i.e.*, the use of pesticides, fertilizers, and soil improvement. The larger tobacco farming area, the larger household size or the farther the distance to a township, the more farmers tend to adopt technology combinations involving pesticides and fertilizers.

The empirical results show that when only observable factors are considered, the estimation of the outcome equation will result in sample selection bias. The empirical results also show some inefficiencies in the adoption behaviour of additional MATs by tobacco farmers. Taking the adoption of three additional technologies as the baseline, the adoption of technology combinations involving pesticides and fertilizers and involving fertilizers and soil improvement had a significant positive impact on the IPHL. Furthermore, the adoption of technology combinations involving pesticides and fertilizers also had a significant positive impact on both YPM and ASPT, indicating that a yield effect and quality-enhancement effect were produced, and the positive impact on IPHL was relatively greater. We found that although most tobacco farmers adopt a combination of the three additional technologies, it was not the best income choice. Some researchers has reported similar findings. For example, Di Falco and Veronesi (2013) studied the strategies adopted by farmers in the Nile basin in Ethiopia to adapt to climate changes, Manda et al. (2016) studied the adoption of SAPs by farmers in Zambia, and Ng'ombe, Kalinda, and Tembo (2017) studied the adoption of conservation farming (CF) practices by farmers in Zambia. This issue deserves constant attention.

5.2 Policy Implications

Based on our research conclusions, we can infer some meaningful policy implications. First, the adoption of additional pesticide and fertilizer combination can not only significantly improve the yield per mu of tobacco, but also significantly improve the quality grade of tobacco, which can increase the sales revenue of tobacco farmers. Therefore, tobacco farmers should put in additional pesticides and fertilizers appropriately based on the implementation of standardized technology system while considering the specific characteristics of the plot and pest situation. Second, because technical training can significantly increase the professional knowledge of tobacco farmers and reduce inefficient additional technology investments, CTC should further strengthen training for tobacco farmers, especially for tobacco farmers far away from tobacco technology extension stations. Third, the combination of fertilizer and soil improvement technology is the second highest income scheme just after the combination of pesticide and fertilizer, although the investment of soil improvement technology is comparatively large and the return period is long, the negative externality of environment is small. The government should give tobacco farmers technical subsidies for soil improvement, stabilize land lease term and other policy support, in order to promote tobacco farmers to adopt soil improvement technology and give overall consideration between the current income growth and sustainable development.

Acknowledgements

We are very grateful to Chongqing Tobacco Science Research Institute for providing us with a lot of data and guidance on tobacco production technology.

References

- Abate, G. T., Bernard, T., Brauw, A. D., & Minot, N. (2018). The impact of the use of new technologies on farmers' wheat yield in Ethiopia: Evidence from a randomized control trial. *Agricultural Economics*, *49*, 409-421. <https://doi.org/10.1111/agec.12425>
- Abdulai, A., & Huffman, W. (2014). The adoption and impact of soil and water conservation technology: An endogenous switching regression application. *Land Economics*, *90*, 26-43. <https://doi.org/10.3368/le.90.1.26>
- 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. <https://doi.org/10.1016/j.ecolecon.2019.03.023>
- Ainembabazi, J. H., Abdoulaye, T., Feleke, S., Alene, A., Donsop-Nguezet, P. M., Ndayisaba, P. C., ... Manyong, V. (2018). Who benefits from which agricultural research-for-development technologies? Evidence from

- farm household poverty analysis in Central Africa. *World Development*, 108, 28-46. <https://doi.org/10.1016/j.worlddev.2018.03.013>
- Amadu, F. O., McNamara, P. E., & Miller, D. C. (2020). Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. *World Development*, 125, 104692. <https://doi.org/10.1016/j.worlddev.2019.104692>
- Appau, A., Drope, J., Goma, F., Magati, P., Labonte, R., Makoka, D., ... Lencucha, R. (2020). Explaining why farmers grow tobacco: Evidence from Malawi, Kenya, and Zambia. *Nicotine and Tobacco Research*, 22, 2238-2245. <https://doi.org/10.1093/ntr/ntz173>
- Appau, A., Drope, J., Witoelar, F., Chavez, J. J., & Lencucha, R. (2019). Why do farmers grow tobacco? A qualitative exploration of farmers perspectives in Indonesia and Philippines. *International Journal of Environmental Research and Public Health*, 16(13), 2330. <https://doi.org/10.3390/ijerph16132330>
- Beaman, L., Karlan, D., Thuysbaert, B., & Udry, C. (2013). Profitability of fertilizer: Experimental evidence from female rice farmers in Mali. *American Economic Review*, 103, 381-386. <https://doi.org/10.1257/aer.103.3.381>
- Binswanger, H. P., & Ruttan, V. W. (1978). *Induced innovation: Technology, institutions, and development*. London: The Johns Hopkins University Press.
- Briones, R. M. (2015). Small farmers in high-value chains: Binding or relaxing constraints to inclusive growth? *World Development*, 72, 43-52. <https://doi.org/10.1016/j.worlddev.2015.01.005>
- Cafer, A. M., & Rikoon, J. S. (2018). Adoption of new technologies by smallholder farmers: the contributions of extension, research institutes, cooperatives, and access to cash for improving tef production in Ethiopia. *Agriculture and Human Values*, 35, 685-699. <https://doi.org/10.1007/s10460-018-9865-5>
- Deb, P., & Trivedi, P. K. (2006a). Maximum simulated likelihood estimation of a negative binomial regression model with multinomial endogenous treatment. *Stata Journal*, 6, 246-255. <https://doi.org/10.1177/1536867X0600600206>
- Deb, P., & Trivedi, P. K. (2006b). Specification and simulated likelihood estimation of a non-normal treatment-outcome model with selection: Application to health care utilization. *Econometrics Journal*, 9, 307-331. <https://doi.org/10.1111/j.1368-423X.2006.00187.x>
- Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics*, 89(4), 743-766. <https://doi.org/10.3368/le.89.4.743>
- Di Falco, S., Bezabih, M., & Yesuf, M. (2010). Seeds for livelihood: Crop biodiversity and food production in Ethiopia. *Ecological Economics*, 69(8), 1695-1702. <https://doi.org/10.1016/j.ecolecon.2010.03.024>
- Dimara, E., & Skuras, D. (1998). Adoption of new tobacco varieties in Greece: Impacts of empirical findings on policy design. *Agricultural Economics*, 19(3), 297-307. [https://doi.org/10.1016/S0169-5150\(98\)00041-3](https://doi.org/10.1016/S0169-5150(98)00041-3)
- Emerick, K., de Janvry, A., Sadoulet, E., & Dar, M. H. (2016). Technological innovations, downside risk and the modernization of agriculture. *American Economic Review*, 106, 1537-1561. <https://doi.org/10.1257/aer.20150474>
- Feder, G. (1982). Adoption of Interrelated Agricultural Innovations: Complementarity and the impacts of risk, scale, and credit. *American Journal of Agricultural Economics*, 64, 94-101. <https://doi.org/10.2307/1241177>
- Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33, 255-297. <https://doi.org/10.1086/451461>
- Gao, Y., Niu, Z. H., Yang, H. R., & Yu, L. L. (2019). Impact of green control techniques on family farms' welfare. *Ecological Economics*, 61, 91-99. <https://doi.org/10.1016/j.ecolecon.2019.03.015>
- Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change*, 80, 525-540. <https://doi.org/10.1016/j.techfore.2012.08.007>
- Kassie, M., Marennya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. *Journal of Agricultural Economics*, 69(1), 76-95. <https://doi.org/10.1111/1477-9552.12221>

- Kassie, M., Teklewold, H., Jaleta, M., Marennya, P., & Erenstein, O. (2015a). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy*, *42*, 400-411. <https://doi.org/10.1016/j.landusepol.2014.08.016>
- Kassie, M., Teklewold, H., Marennya, P., Jaleta, M., & Erenstein, O. (2015b). Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. *Journal of Agricultural Economics*, *66*(3), 640-659. <https://doi.org/10.1111/1477-9552.12099>
- Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American Journal of Agricultural Economics*, *83*(1), 35-51. <https://doi.org/10.1111/0002-9092.00135>
- Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H., & Alene, A. D. (2018). Adoption and welfare impacts of multiple agricultural technologies: Evidence from eastern Zambia. *Agricultural Economics*, *49*(5), 599-609. <https://doi.org/10.1111/agec.12445>
- Kimbi, T. G., Akpo, E., Kongola, E., Ojiewo, C. O., Vernoooy, R., Muricho, G., & Tabo, R. (2021). A probit analysis of determinants of adoption of improved sorghum technologies among farmers in Tanzania. *Journal of Agricultural Science*, *13*(1), 73-87. <https://doi.org/10.5539/jas.v13n1p73>
- Lee, D. R. (2005). Agricultural sustainability and technology adoption: Issues and policies for developing countries. *American Journal of Agricultural Economics*, *8*(5), 1325-1334. <https://doi.org/10.1111/j.1467-8276.2005.00826.x>
- Magati, P., Lencucha, R., Li, Q., Drope, J., & Zulu, R. (2019). Costs, contracts and the narrative of prosperity: An economic analysis of smallholder tobacco farming livelihoods in Kenya. *Tobacco Control*, *28*(3), 268-273. <https://doi.org/10.1136/tobaccocontrol-2017-054213>
- Makoka, D., Drope, J., Appau, A., Labonte, R., Li, Q., Goma, F., ... Lencucha, R. (2017). Costs, revenues and profits: An economic analysis of smallholder tobacco farmer livelihoods in Malawi. *Tobacco Control*, *26*(6), 634-640. <https://doi.org/10.1136/tobaccocontrol-2016-053022>
- Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics*, *67*(1), 130-153. <https://doi.org/10.1111/1477-9552.12127>
- Martey, E., Etwire, P. M., & Abdoulaye, T. (2020). Welfare impacts of climate-smart agriculture in Ghana: Does row planting and drought-tolerant maize varieties matter? *Land Use Policy*, *95*, 104622. <https://doi.org/10.1016/j.landusepol.2020.104622>
- Mastenbroek, A., Sirutyte, I., & Sparrow, R. (2021). Information barriers to adoption of agricultural technologies: Willingness to pay for certified seed of an open pollinated maize variety in northern Uganda. *Journal of Agricultural Economics*, *72*, 180-201. <https://doi.org/10.1111/1477-9552.12395>
- Michler, J. D., Tjernström, E., Verkaart, S., & Mausch, K. (2019). Money matters: The role of yields and profits in agricultural technology adoption. *American Journal of Agricultural Economics*, *101*, 710-731. <https://doi.org/10.1093/ajae/aay050>
- Midingoyi, S. K. G., Kassie, M., Muriithi, B., Diiro, G., & Ekesi, S. (2019). Do farmers and the environment benefit from adopting integrated pest management practices? Evidence from Kenya. *Journal of Agricultural Economics*, *70*, 452-470. <https://doi.org/10.1111/1477-9552.12306>
- Mishra, A. K., Khanal, A. R., & Pedde, V. O. (2017). Is direct seeded rice a boon for economic performance? Empirical evidence from India. *Food Policy*, *73*, 10-18. <https://doi.org/10.1016/j.foodpol.2017.08.021>
- Mutale, G., Kalinda, T., & Kuntashula, E. (2017). Factors affecting the joint adoption of herbicides and conservation tillage technologies among smallholder farmers in Zambia. *Journal of Agricultural Science*, *9*(12), 205-222. <https://doi.org/10.5539/jas.v9n12p205>
- Mutenje, M., Kankwamba, H., Mangisonib, J., & Kassie, M. (2016). Agricultural innovations and food security in Malawi: Gender dynamics, institutions and market implications. *Technological Forecasting and Social Change*, *103*, 240-248. <https://doi.org/10.1016/j.techfore.2015.10.004>
- Ng'ombe, J. N., Kalinda, T. H., & Tembo, G. (2017). Does adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. *Agrekon*, *56*(2), 205-221. <https://doi.org/10.1080/03031853.2017.1312467>

- Omara, H., Odongo, W., & Kule, E. K. (2021). Adoption of environmentally friendly agricultural technologies among smallholder farmers: The case of rocket barn technology in flue-cured tobacco curing in Uganda. *Land Degradation and Development*, 32, 965-974. <https://doi.org/10.1002/ldr.3765>
- Pannell, D. J., Llewellyn, R. S., & Corbeels, M. (2014). The farm-level economics of conservation agriculture for resource-poor farmers. *Agriculture, Ecosystems and Environment*, 187, 52-64. <https://doi.org/10.1016/j.agee.2013.10.014>
- Rogers, E. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.
- Ruttan, V. W., & Hayami, Y. (1984). Toward a theory of induced institutional innovation. *Journal of Development Studies*, 20, 203-223. <https://doi.org/10.1080/00220388408421914>
- Scoones, I., Mavedzenge, B., Murimbarimba, F., & Sukume, C. (2018). Tobacco, contract farming, and agrarian change in Zimbabwe. *Journal of Agrarian Change*, 18(1), 22-42. <https://doi.org/10.1111/joac.12210>
- Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), 159-209. <https://doi.org/10.3982/ECTA7749>
- Tambo, J. A., & Mockshell, J. (2018). Differential impacts of conservation agriculture technology options on household income in sub-Saharan Africa. *Ecological Economics*, 151, 95-105. <https://doi.org/10.1016/j.ecolecon.2018.05.005>
- Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics*, 93, 85-93. <https://doi.org/10.1016/j.ecolecon.2013.05.002>
- Tesfaye, W., Blalock, G., & Tirivayi, N. (2020). Climate-smart innovations and rural poverty in Ethiopia: Exploring impacts and pathways. *American Journal of Agricultural Economics*, 103(3), 878-899. <https://doi.org/10.1111/ajae.12161>
- Tufa, A. H., Alene, A. D., Manda, J., Akinwale, M. G., Chikoye, D., Feleke, S., ... Manyong, V. (2019). The productivity and income effects of adoption of improved soybean varieties and agronomic practices in Malawi. *World Development*, 124, 104631. <https://doi.org/10.1016/j.worlddev.2019.104631>
- Wu, J. J., & Babcock, B. A. (1998). The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics*, 80, 494-511. <https://doi.org/10.2307/1244552>
- Zeweld, W., Van Huylenbroeck, G., Tesfay, G., Azadi, H., & Speelman, S. (2020). Sustainable agricultural practices, environmental risk mitigation and livelihood improvements: Empirical evidence from Northern Ethiopia. *Land Use Policy*, 95, 103799. <https://doi.org/10.1016/j.landusepol.2019.01.002>

Appendix A

Table A1. Distribution of questionnaires in 12 districts and counties

District/County	Number of questionnaires(n)	Valid questionnaires(n)	Percentage proportion (%)
Youyang County	65	56	86.15%
Wulong District	55	45	81.82%
Pengshui County	90	55	61.11%
Fuling District	15	13	86.67%
Qianjiang District	45	33	73.33%
Nanchuan District	10	10	100%
Fengdu County	35	24	68.57%
Shizhu County	30	17	56.67%
Wushan County	60	38	63.33%
Wuxi County	35	35	100%
Fengjie County	45	43	95.56%
Wanzhou District	15	15	100%
Total	500	384	76.80%

Note. n: sample size.

Table A2. Descriptive statistics by IPM & BF, BF & SI, IPM & BF & SI

Variables	IPM & BF	BF & SI	IPM & BF & SI
	----- Mean -----		
YPM	117.669 (2.594)	112.614 (2.848)	112.196 (1.734)
ASPT	26.937 (0.338)	28.347 (0.205)	27.701 (0.137)
IPHL	6.677 (0.657)	5.82 (0.444)	5.966 (0.26)
Gender	0.9 (0.048)	0.929 (0.031)	0.932 (0.016)
Age	50.55 (1.129)	49.343 (0.785)	49.841 (.449)
Education	2.75 (0.123)	2.5 (0.073)	2.701 (0.047)
Years	22.15 (1.721)	16.443 (0.997)	21.263 (0.63)
Homesize	5.325 (0.249)	4.771 (0.154)	4.869 (0.091)
Planter	2.2 (0.114)	2.143 (0.089)	2.048 (0.036)
Area	43.825 (3.97)	38.443 m(3.128)	37.496 (1.365)
Distance1	11.803 (1.606)	6.086 (0.504)	8.89 (0.437)
Loan	0.425 (0.079)	0.414 (0.059)	0.442 (0.031)
Train	5.325 (0.439)	6.086 (0.285)	4.952 (0.152)
Labour	0.683 (0.035)	0.689 (0.028)	0.7 (0.015)
Distance2	6.1 (0.724)	3.167 (0.335)	5.759 (0.327)
Ground	0.657 (0.046)	0.657 (0.04)	0.749 (0.018)
Rentedfarmland	0.674 (0.051)	0.571 (0.039)	0.697 (0.036)
Observations	40	70	251

Note. Standard errors in parentheses.

Table A3. Test on the validity of selection instruments

Variables	IPM & BF	BF & SI	IPM & BF & SI
Ln YPM	F(3, 26) = 0.25	F(3, 56) = 1.53	F(3, 237) = 0.32
Ln ASPT	F(3, 26) = 0.66	F(3, 56) = 0.68	F(3, 237) = 0.40
Ln IPHL	F(3, 26) = 0.96	F(3, 56) = 1.97	F(3, 237) = 1.98
Observations	40	70	251

Table A4. Second stage estimates for YPM, ASPT and IPHL

Variables	Ln YPM	Ln ASPT	Ln IPHL
Age	-0.00192 (0.00196)	-0.00162*** (0.0000994)	-0.00511*** (0.000650)
Education	-0.00631 (0.0185)	0.00419*** (0.000909)	0.0408*** (0.00564)
Years	-0.000567 (0.00139)	0.000747*** (0.0000743)	-0.00506*** (0.000505)
Homesize	-0.0000780 (0.0106)	0.00263*** (0.000523)	0.0133*** (0.00328)
Planter	-0.0202 (0.0212)	-0.0112*** (0.00117)	-0.515*** (0.00573)
Area	-0.00166*** (0.000604)	0.0000775** (0.0000309)	0.0197*** (0.000174)
Distance1	-0.00257 (0.00182)	-0.000321*** (0.0000936)	-0.00305*** (0.000656)
Loan	-0.0213 (0.0271)	-0.0242*** (0.00147)	0.0170* (0.00978)
Train	0.00522 (0.00515)	0.00616*** (0.000234)	0.0146*** (0.00219)
Labour	-0.0694 (0.0628)	0.0397*** (0.00339)	-0.0374 (0.0231)
Constant	4.982*** (0.137)	3.334*** (0.00708)	2.011*** (0.0420)

Note. *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses.

Table A5. Robustness test results

Model Package	OLS		
	Ln YPM	Ln ASPT	Ln IPHL
IPM & BF	0.082*** (2.567)	-0.032** (-2.30)	0.088* (1.72)
BF & SI	-0.014 (-0.43)	0.029*** (3.24)	-0.024 (-0.55)
IPM & BF & SI	-0.028 (-1.09)	-0.006 (-0.65)	-0.024 (-0.68)

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. z-values are in parentheses. Due to the implementation of tobacco production contract management, the values of ASPT in the table were affected to some extent, robustness check can be judged just by values of YPM and IPHL.

Copyrights

Copyright for this article is retained by the author(s), with first publication rights granted to the journal.

This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (<http://creativecommons.org/licenses/by/4.0/>).