Ecological Economics 161 (2019) 91–99

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

Impact of green control techniques on family farms' welfare

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ARTICLE INFO

Keywords:
Green Control Techniques
Welfare Effect
Endogenous Switching Regression Model
Multinomial Treatment Effects Model

ABSTRACT

Using survey data of 375 family farms in five provinces of the Huang-Huai-Hai Plain, this paper conducts a comprehensive measurement of family farms' welfare within the framework of the capability approach theory. Furthermore, using an endogenous switching regression model and a multinomial treatment effects model, this paper evaluates the impact of the adoption or non-adoption of green control techniques on family farms' welfare and estimate the welfare effects of the degree and timing of adoption. This research finds that the average treatment effect on family farm welfare with and without adopting green control techniques is significant, at 0.084 and 0.046, respectively. Therefore, green control techniques help to improve the welfare level of family farms. Compared with family farms that do not adopt green control techniques, the welfare level of family farms adopting a high or low degree of green control techniques increases by 22.63% and 16.42%, respectively, and the welfare level of family farms given the early or late adoption of green control techniques increases by 5.87% and 7.57%, respectively. Therefore, the welfare effect of a high degree of adoption on family farms is greater, and the welfare level of family farms with late adoption is higher.

1. Introduction

Chemical pesticides are an important means of agricultural production. Their use is essential for preventing and controlling pests and for stabilizing high yields. However, the current average usage of chemical pesticides per unit area in China is 2.5 to 5 times higher than that in agriculturally developed countries (Jin et al., 2016). In addition, nonstandard behaviors such as increasing the dosage and frequency of chemical pesticide use and shortening the intervals between doses are ubiquitous (Gao et al., 2019). Chemical pesticides have been transformed from being tools for maintaining and increasing production to being one of the “culprits” affecting the quality and safety of agricultural products, ecology, the environment, and agricultural production (Yin et al., 2018). To this end, China proposes adhering to policies reducing and controlling the use of pesticides and striving to achieve zero growth in the use of pesticides by 2020 to promote the sustainable development of agriculture.[1] Specifically, China has begun to promote green control techniques (GCT), which is a Chinese integrated pest management (IPM) concept. Based on the plant protection policy of “prevention-oriented, comprehensive prevention and control” and the concept of “green plant protection”, GCT prioritizes the adoption of resource-saving and environmentally friendly technical measures such as ecological regulation, biological control, physical control, and scientific pesticide use. However, in China, GCT still focuses on experimental demonstrations and small-scale implementation, and there have been many challenges extending GCT and applying it to large areas (Wang et al., 2015).

Successful extension and application of GCT cannot be separated from the support and guidance of policy, and the market mechanism must also play a decisive role. The improvement of farmers' household welfare is not only a prerequisite for successfully extending GCT but also an important goal when promoting and applying GCT. However, under the impact of the market economy and agricultural modernization policies, China's rural households are becoming increasingly divided into traditional farm households and family farms (Gao et al., 2017a). In terms of land, traditional households mainly rely on their

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[1] General Office of the State Council: “Opinions on Accelerating the Transformation of Agricultural Development”, http://www.gov.cn/zhengce/2016-01/27/content_5036698.htm, January 27, 2016;
General Office of the State Council: “Opinions on Innovating the Institutional Mechanism to Promote Green Agricultural Development”, http://www.gov.cn/xinwen/2017-09/30/content_5228960.htm, September 30, 2017.

https://doi.org/10.1016/j.ecolecon.2019.03.015
Received 1 September 2018; Received in revised form 29 January 2019; Accepted 14 March 2019

own land, which they supplement with leased land, whereas the land of family farms is primarily leased land supplemented by their own land. Considering financial status, traditional households rely on their own funds and often lack a clear return on capital, whereas family farms need outside investment combined with their own capital and have a clear goal regarding return on capital. The views on labor also differ: traditional households mainly rely on family members, with an occasional need for outside labor from neighbors, while family farms rely mainly on their own labor force. In addition, considering the nature of the labor operating these farms, traditional households rely mainly on productive labor, while family farms make use of both productive and managerial labor. In terms of product attributes, traditional households produce for the farmer's living needs, and family farms produce mainly for profit. Thus, it can be seen that family farms are different from traditional households in terms of production factors such as land, capital and labor, the nature of labor and the product attributes of the households (Gao et al., 2013). Meanwhile, moderate-scale family farms are a trend within China's future agricultural development, and they will play a leading role for traditional farmers in green development (He, 2016).

Based on the main conclusions of the capability approach theory (CAT) and related literature, this article takes 375 family farms in the Huang-Huai-Hai Plain as an example and comprehensively assesses their welfare level. On this basis, the endogenous switching regression model (ESRM) was used to explore the effects of GCT adoption behaviors on family farms' welfare, and a multinomial treatment effects model (MTEM) was employed to verify whether family farms' degree and timing of adopting GCT will lead to differences in their welfare.

Compared with previous studies, the main contributions of this article are as follows. First, taking the welfare effect of family farms' GCT adoption behavior as an example, this article expands the existing research objects. Second, it discusses the effects of family farms' GCT adoption behavior on their comprehensive welfare, which fully reflects the welfare effects of family farms' GCT adoption. Third, the article focuses on the differences in family farms' welfare that may result from the degree and timing of the adoption of GCT, all of which deepen the content of existing research.

2. Review of the literature

To empirically analyze the welfare effects of farmers' GCT adoption behavior, we must first clarify what welfare is and how to measure it. The understanding of welfare has generally experienced three stages. The first stage is the old welfare economics represented by Pigou (1933), which divided welfare into economic welfare and general welfare. Economic welfare can be directly measured by currency, but general welfare cannot be measured. The second stage is the new welfare economics represented by Pareto et al. (1971), Kaldor (1939), and Hicks (1939). This stage starts with Pareto optimality, focuses on economic welfare, and believes that economic changes will produce welfare beneficiaries and welfare losers. Compensating for the welfare of the losers creates economic changes that can bring about economic growth. The third stage is modern welfare economics represented by Sen (1979, 1981, 1999). This stage extends the concept of welfare and considers welfare to include not only economic welfare but also noneconomic welfare.

Corresponding to the three stages of understanding welfare, there are three different forms of welfare measurement. Mmbando et al. (2015), Chen and Zhai (2015), and Perge and McKay (2016) measured the welfare of rural households within the framework of the old welfare economics, using economic indicators measured directly by available currencies, such as household income and consumption. Miao (2014) and Luo et al. (2017) followed the ideas of new welfare economics, starting with price changes, incorporating the concept of welfare compensation, and measuring welfare using consumer surplus and producer surplus. Gao and Qiao (2011), Li et al. (2015), and Wei and Zhang (2016), based on the CAT of Sen (1999), constructed an indicator system including family living status, health, social status and psychological status in addition to family economic condition to measure welfare.

Under the premise of determining how to measure welfare, existing studies have analyzed the welfare effects of water-saving technologies, improved varieties, rainwater harvesting technologies, fish-rice integrated farming systems, straw resource utilization technologies, corn-soybean rotation systems and many other adoption behaviors. For example, Faltermeier and Abdulai (2009) confirmed that the adoption of water-saving technologies by households in Ghana will increase their output, but their income will not change significantly. Becerril and Abdulai (2010) found that after planting improved maize varieties, the probability of Mexican farmers falling below the poverty line will be reduced by 19% to 31%, and their per capita consumer spending will be increased by 136–173 Mexican pesos; in Malawi, farmers' household income, maize consumption, and asset holdings will be increased by 0.48%, 0.34%, and 0.24%, respectively (Bezu et al., 2014); furthermore, income per acre and the per capita consumption expenditure of farmer households in East Zambia will be increased by 66.9 to 78.9 and 186.8 to 324.69 Zambian kwachas, respectively (Khonje et al., 2015). After planting improved varieties of chickpeas and legumes, farmers' household expenditures in Ethiopia and Tanzania will be increased by 20.9% and 99.4%, respectively (Asfaw et al., 2012). After planting improved wheat varieties, per capita household consumption expenditures in Ethiopian households will be increased by 158.85 to 177.58 Ethiopian rupees, and the level of food safety will be increased by 2.7% to 4.5% (Shiferaw et al., 2014). Zingiro et al. (2014) noted that the annual income of Rwandan farmers who adopted rainwater harvesting technology is US$149 higher than that of farmers without rainwater harvesting technology. Saiful Islam et al. (2015) believe that the annual household income of farmers who adopted a fish-rice integrated farming system in Bangladesh is 22% higher than that of non-adopting households, and the consumption of aquatic products is 1.3 to 2 times that of non-adopting farmers. Yan et al. (2016) confirmed that the economic, ecological and health welfare of farmers who adopted straw resource utilization technology in Hubei Province were improved by 16.7%, 34.9%, and 45.6%, respectively. The study by Manda et al. (2017) shows that the cost of production for Zambian farmers adopting a corn-soybean crop rotation system will be reduced by 26% to 32% compared with that of farmers who did not adopt a corn-soybean rotation system. There has been no report on the welfare effects of farmer households' GCT adoption behaviors.

There is still room for more in-depth investigation in existing studies. (1) With economic and social development, the connotation of welfare has developed into a multidimensional perspective. However, most of the existing studies focus only on the economic welfare effect of farmers' adoption behavior, which means that existing studies cannot fully reflect the comprehensive welfare effect of farmer' adoption behavior. (2) Farmers with different degrees and timing of adoption may have different technology adoption costs, pest control effects, and production and operating risks, which may lead to differences in their welfare levels (Tambo and Wünscher, 2017). Most of the existing studies focus on analyzing the welfare effects of farmers' adoption behavior (adoption or not), but studies that analyze the impact of farmers' adoption timing and degree on their welfare are still very scarce in the literature.

3. Research methods

3.1. Endogenous switching regression model

To reveal the impact of family farms' GCT adoption behavior on their welfare, it is necessary to measure the average treatment effect on the treated (ATT) of the welfare of family farms that adopted GCT and the average treatment effect on the untreated (ATU) of the welfare of family farms that did not adopt GCT. Most existing studies use propensity score matching (PSM) (Kassie et al., 2011; Kebebe and Shibru, 2017; Owusu et al., 2011) to measure ATT and ATU. However, PSM can correct the problem of sample selection bias caused by observable factors only and cannot account for unobservable factors (Fischer and Qaim, 2012). Therefore, this article uses ESRM to effectively avoid sample selection bias.

ESRM is divided into two stages. In the first stage, a decision equation is constructed to analyze the factors influencing family farms' GCT adoption behavior. Its specific form is as follows:

$$P_i^* = Z_i\alpha + \mu_i \qquad P_i = \begin{cases} 1 & \text{if } P^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

P_i is the observed value of GCT adoption behavior for family farm i; $P = 1$ means adopting GCT, and $P = 0$ means not adopting GCT. Z_i represents the influencing factor vector of family farms' GCT adoption behavior. α is the estimated coefficient of Z_i, and μ_i is a random error term.

The second stage requires the construction of an outcome equation that can be used to analyze the influencing factors of a family farm's welfare level. Its specific form is as follows:

$$Y_{i0} = \gamma_0 X_{i0} + \varepsilon_{i0} \quad \text{if } P = 0$$

$$Y_{i1} = \gamma_1 X_{i1} + \varepsilon_{i1} \quad \text{if } P = 1 \tag{2}$$

where Y_{i0} and Y_{i1} are defined as the welfare levels of family farms that did not and that did adopt GCT, respectively. X_{i0} and X_{i1} represent the influencing factor vectors of the welfare level of family farms that did not adopt and that did adopt GCT. γ_0 and γ_1 are their regression coefficients. ε_{i0} and ε_{i1} are random error terms.

However, in an actual situation, we cannot simultaneously measure the welfare level of family farm i in the two cases of adopting and not adopting GCT. The welfare level of family farm i depends on formula (1). If OLS estimation is performed directly on Eq. (2), there will be a sample selection bias problem caused by observable and unobservable factors, resulting in biased estimation results. Therefore, this paper fully considers possible factors that affect the welfare level of family farms and controls the sample selection bias caused by observable factors by reducing missing variables. Meanwhile, this paper corrects the problem of sample selection bias caused by unobservable factors by constructing a covariance matrix Ω of the error terms of decision and resulting equations, i.e.:

$$\Omega = \begin{bmatrix} \sigma_\mu^2 & \sigma_{\mu 1} & \sigma_{\mu 0} \\ \sigma_{\mu 1} & \sigma_1^2 & . \\ \sigma_{\mu 0} & . & \sigma_0^2 \end{bmatrix} \tag{3}$$

In formula (3), ${\sigma_\mu}^2 = var(\mu_i)$, ${\sigma_1}^2 = var(\varepsilon_{i1})$, ${\sigma_0}^2 = var(\varepsilon_{i0})$, $\sigma_{\mu 1} = cov(\mu_i, \varepsilon_{i1})$, $\sigma_{\mu 0} = cov(\mu_i, \varepsilon_{i0})$. Because the random disturbance term μ_i of the decision equation and the random error terms ε_{i0}, ε_{i1} of the outcome equation are related to each other, the conditional expectations of ε_{i0} and ε_{i1} can be expressed as:

$$E(\varepsilon_{i1} \mid P = 1) = \sigma_{\mu 1}\frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} = \sigma_{\mu 1}\lambda_{i1} \tag{4}$$

$$E(\varepsilon_{i0} \mid P = 0) = -\sigma_{\mu 0}\frac{\phi(Z_i a)}{1 - \Phi(Z_i a)} = \sigma_{\mu 0}\lambda_{i0} \tag{5}$$

where ϕ and Φ represent a standard normal probability density function and a cumulative distribution function, respectively. $\lambda_{i1} = \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$, $\lambda_{i0} = \frac{-\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$ represent inverse Mills ratios of the family farms that adopted GCT and that did not adopt GCT, respectively, which can correct the sample selection bias caused by unobservable factors.

We introduce ε_{i0} and ε_{i1} into Eq. (2). After correcting the outcome equation, we obtain:

$$Y_{i0} = \gamma_{i0} X_{i0} + \sigma_{\mu 0}\lambda_{i0} + \omega_{i0} \quad \text{if } P = 0$$

$$Y_{i1} = \gamma_{i1} X_{i1} + \sigma_{\mu 1}\lambda_{i1} + \omega_{i1} \quad \text{if } P = 1 \tag{6}$$

In formula (6), $\sigma_{\mu 0}\lambda_{i0}$ and $\sigma_{\mu 1}\lambda_{i1}$ are sample selection deviation correction terms, and ω_{i0} and ω_{i1} are random error terms. Other items are defined as in Eq. (2). In addition, when the covariance correlation coefficients $\rho_0\left(\frac{\sigma_{\mu 0}}{\sigma_\mu \sigma_0}\right)$ or $\rho_1\left(\frac{\sigma_{\mu 1}}{\sigma_\mu \sigma_1}\right)$ between the random error terms in the decision equation and outcome equation are significantly nonzero, it indicates that there are unobservable factors that cause sample selection bias (Ma and Abdulai, 2016).

Hence, under the framework of ESRM, the family farm's welfare treatment effect can be expressed as:

$$E(Y_{i1} \mid P = 1; X) = \gamma_1 X_{i1} + \sigma_{\mu 1}\lambda_{i1} \tag{7a}$$

$$E(Y_{i0} \mid P = 0; X) = \gamma_0 X_{i0} + \sigma_{\mu 0}\lambda_{i0} \tag{7b}$$

$$E(Y_{i0} \mid P = 1; X) = \gamma_0 X_{i1} + \sigma_{\mu 0}\lambda_{i1} \tag{7c}$$

$$E(Y_{i1} \mid P = 0; X) = \gamma_1 X_{i0} + \sigma_{\mu 1}\lambda_{i0} \tag{7d}$$

where (7a) and (7b) represent the welfare treatment effects of family farms that adopted GCT and of those that did not adopt GCT, respectively. Both effects can be observed in actual situations. (7c) represents the hypothetical welfare treatment effect of family farms that adopted GCT if they had not adopted this technology, and (7d) indicates the hypothetical welfare treatment effect of family farms that did not adopt GCT if they had adopted this technology. Because (7c) and (7d) are not observable in the actual situation and are inconsistent with the facts, they are defined as counterfactuals. The welfare average treatment effect of family farms that adopted GCT is the difference between (7a) and (7c), and the welfare average treatment effect of family farms without adopting GCT is the difference between (7d) and (7b), i.e.:

$$\begin{aligned} ATT &= (7a) - (7c) = E(Y_{i1} \mid P = 1) - E(Y_{i0} \mid P = 1) \\ &= X_{i1}(\gamma_1 - \gamma_0) + \lambda_{i1}(\sigma_{\mu 1} - \sigma_{\mu 0}) \end{aligned} \tag{8}$$

$$\begin{aligned} ATU &= (7d) - (7b) = E(Y_{i1} \mid P = 0) - E(Y_{i0} \mid P = 0) \\ &= X_{i0}(\gamma_1 - \gamma_0) + \lambda_{i0}(\sigma_{\mu 1} - \sigma_{\mu 0}) \end{aligned} \tag{9}$$

3.2. Multinomial treatment effects model

To further verify the difference in welfare caused by the degree and timing of GCT adoption in family farms, this article classifies family farms into those adopting GCT to high degree (earlier adoption) and those adopting to a low degree (later adoption) and compares them with family farms that did not adopt GCT. This article has two sets of decision variables, i.e., a high degree of adoption (earlier adoption) and non-adoption and a low degree of adoption (later adoption) and non-adoption. Hence, there are inherent endogeneity problems. To estimate the effect of multivariate endogenous treatment variables on the outcome variables and effectively avoid sample selection bias, this article uses the MTEM proposed by Deb and Trivedi (2006). This model also includes two stages: a decision equation and an outcome equation. The decision equation is used to estimate the probability that family farm i chooses the degree (timing) of adoption (m), which is:

$$\Pr(P_{vi} \mid Z_i, l_i) = \frac{\exp(Z_i'\alpha_m + l_{im})}{1 + \sum_{k=1}^{M}\exp(Z_i'\alpha_k + l_{ik})} \tag{10}$$

The outcome equation is used to estimate how the different degrees (timing) of adoption of GCT affect the welfare of family farms that adopted GCT in comparison with family farms that did not adopt GCT. The specific formula is as follows:

$$E(Y_i \mid P_{vi}, Z_i, L_i) = \gamma_i X_i + \sum_{m=1}^{M}\delta_m P_{vi\,m} + \sum_{m=1}^{M}\lambda_m l_{im} \tag{11}$$

In formula (11), P_{vi} denotes the observation value of adoption degree (timing) of GCT of family farm *i*. $P_{vi} = 1$ indicates that the adoption degree is high (earlier adoption) or low (later adoption), and $P_{vi} = 0$ indicates that the household did not adopt GCT. $m = 0, 1, 2,$ indicate non-adoption, a high degree of adoption (earlier adoption) and a low degree of adoption (later adoption), respectively. $Z_i^{'}$ represents the vector of factors influencing the GCT adoption behavior of family farm *i*, and α_m is the regression coefficient of $Z_i^{'}$. δ_m is the regression coefficient of the welfare effect when family farm *i* chooses *m* compared to a family farm that did not adopt GCT. l_{im} represents invisible factors that affect both family farm *i* choosing *m* and its welfare. λ_m is the regression coefficient of l_{im}.

4. Variable selection, measurement and data description

4.1. Variable selection and measurement

4.1.1. Welfare level of family farms

Sen proposed the CAT in the 1980s and 1990s and redefined the concept of welfare. A person's capability refers to combinations of possible functional activities that the person is likely to achieve (Sen, 1999). These functions include activities or conditions in a person's life, such as having a healthy body, good interpersonal relationships, and being able to enjoy proper leisure time. If the functional activities within a person's life constitute that person's welfare, that person's capability reflects real opportunities to obtain benefits and the freedom to make choices around different lifestyles. Sen examined functional activities, considering six aspects when evaluating benefits: income levels, living conditions, health conditions, education and knowledge, social conditions and psychological conditions. This article takes Sen's CAT as the basic framework and expands it. Taking economic conditions, social security, health and leisure and psychological conditions into account, this article constructs a family farm welfare index system. On this basis, family farms' welfare level is calculated with the fuzzy comprehensive evaluation method.[2]

4.1.1.1. Economic conditions. Although many flaws exist in taking economic conditions as a substitute for welfare in theory, it is still an important way to reflect welfare levels (Kawanaka et al., 2014). Compared with family farms that did not adopt GCT, family farms that adopted GCT had reduced crop losses caused by pests and diseases, and the cost of pesticides was reduced. The average net income from farming per mu was significantly higher (Yin et al., 2017). Therefore, this article selects net income from farming per mu to reflect the economic status of family farms.

4.1.1.2. Social security. Social security is an important aspect of farmers' welfare. Devereux (2015) believes that agricultural insurance is an effective tool for social security. Family farms that adopt GCT will more actively insure their agricultural production in response to risks caused by improper use of technology. Therefore, this article selects whether the farm is insured to evaluate the social security status of family farms.

4.1.1.3. Health and Leisure. Participating in leisure activities and maintaining good health both improve people's welfare (Abdul Karim et al., 2010). Family farms that adopt GCT avoid health threats from chemical pesticides, which greatly reduces the time spent on pest and disease control work and frees up time that farmers can use to participate in leisure activities. In view of this, this article measures the health and leisure status of family farms according to their state of health and leisure.

4.1.1.4. Psychological conditions. Although psychological factors cannot be easily quantified, people's perceptions still remain an important part of their welfare (Bonnefon, 2013). Gao and Qiao (2016) noted that farmers' satisfaction with their quality of life is an important aspect of their psychological status. After family farms adopt GCT, their incomes will be raised, and they will also have more leisure time, which may make them feel more satisfied with their quality of life. Therefore, this article selects the degree of satisfaction with life quality as a concrete indicator for evaluating family farms' psychological conditions.

In the measurement of family farm welfare indicators, average net income per mu, Engel's coefficient, and average subsidy per mu are measured based on the average value for the past three years.[3] Whether the farm is insured is indicated as "insured = 1, not insured = 0". Other variables are measured using a 7-point Likert scale.

4.1.2. Treatment variable

The treatment variables in this article include GCT adoption behavior, degree and timing. In terms of adoption, this article measures the number of GCT subtechnologies adopted by family farms. At present, GCT includes four subtechnology types: ecological regulation technology, biological control technology, physical and chemical senility and scientific drug use technology. For the convenience of analysis, when a family farm adopts only one type from among the subtechnologies listed above, the adoption degree of the family farm is defined as low; when the family farm adopts ≥ 2 subtechnology types, the adoption degree of the family farm is defined as high. This article considers the adoption timing based on the subjective feelings of family farmers about the adoption timing.

4.1.3. Controlled variable

Based on the main conclusions of the related literature, this paper selects age, gender, education, risk preference, labor force size, cultivated land area, financial status, frequency of communication with neighbors, media propaganda, agricultural technology department extensions, and supervision of the quality and safety of agricultural products as control variables in the decision equation and outcome equation. Gender, age, education, labor force size and cultivated land area are measured by, respectively, male = 1, female = 0; actual age in 2017; actual years of education completed, number of years of education; the number of family members who can provide labor plus the number of long-term employees; and the actual cultivated land area in 2017. The other variables are all measured by 7-point Likert scales.

4.1.4. Identification variable

To ensure the identifiability of the decision equation and the outcome equation, it is required that at least one control variable in the decision equation not be included in the outcome equation (Coromaldi et al., 2015). Therefore, referring to the research of Di Falco et al. (2011), this article selects distance (km) between a family farm and the nearest agricultural technology extension station (ATES) as the identification variable and tests its robustness.[4] Aside from the identification variable, the control variables of the decision equations and the outcome equations are usually the same (Liu, 2017).

[2] Due to the limitation of length, further tautology is avoided.

[3] If the family farm has been operating for fewer than three years, the average is calculated from the date of commencement of business; if the family farm adopted GCT within the last three years, it is counted from the date of initial adoption.

[4] The test results show that the identification variable is valid, and family farms' knowledge of GCT is significant in the decision equation [$\chi^2 = 169(p = 0.003)$] but not significant in the result equation [$F = 1.33(p = 0.328)$].

4.2. Data description

4.2.1. Data resources

This article selects the five provinces of Hebei, Henan, Anhui, Shandong and Jiangsu in the Huang-Huai-Hai Plain for investigation for the following reasons. First, the agricultural output of these five provinces accounts for 34.2% of China's total production.[5] This plain is an important agricultural production base in China. Second, the number of family farms in the five provinces showed explosive growth, with over 10,000 family farms registered in the industrial and commercial sectors in each province. Third, there are high incidences of pests and diseases in these five provinces and thus a serious need for pest and disease control (Gao et al., 2018). Fourth, since 2017, although there is no clear statistical data for Shandong Province and Henan Province, the GCT coverage rate of major crops in Hebei Province has reached 29.6%,[6] the GCT coverage rate of Anhui's main crops is 28%[7] and that of Jiangsu Province is > 30%.[8] The GCT coverage rates for the above three provinces were all higher than the national average of 27.2%.[9] Hence, this area is selected for investigation under the expectation that it will be representative.

The research was conducted in two phases. The first phase was preliminary research. In June 2017, 30 household farms in Shandong Province were randomly selected for interviews. Based on the preliminary research results, we addressed deficiencies in the questionnaire. The second phase was formal research. From July to September 2017, we adopted a three-stage random sampling method. First, we randomly selected 2 prefecture-level cities in each province. Second, we randomly selected 2 counties (cities, districts) in each prefecture-level city. Finally, 20 household farms were randomly selected from each county (city, district) to receive the questionnaire survey. Questionnaires were filled out by trained graduate students and senior undergraduates by means of household interviews. We issued a total of 400 questionnaires. After excluding questionnaires missing important information, with completion irregularities, or displaying obvious mistakes, 375 valid questionnaires were ultimately obtained. The effective response rate of the questionnaire was 93.75%.

4.2.2. Descriptive statistics

As shown in Table 1, among the 375 family farms, 117 family farms had adopted GCT, accounting for 31%; 68 family farms had a low GCT degree, accounting for 18%; and 86 family farms adopted GCT with late timing, accounting for 23%. Adoption among these farms is basically consistent with the current situation in China: the GCT penetration rate is low, and most farms are characterized by a low degree of adoption and late adoption.

Considering the characteristics of family farms, most of the heads are men, of medium education and in the prime of their lives. Family farms with a cultivated area of 50–150 mu and a labor force of 6 people account for the largest proportion. The indicators above are consistent with the survey results for 2903 family farms conducted by the Ministry of Agriculture in 2015, indicating that the results of this research are representative.

In Table 2, the mean values for economic conditions, social security, health and leisure, and psychological conditions of family farms that adopted GCT are greater than those for family farms that did not adopt GCT. Therefore, the mean value of the welfare level measured by the fuzzy comprehensive evaluation method will also be higher. The abovementioned differences are significant, showing that GCT can help improve the welfare of family farms. However, to specify the welfare effect of family farms' GCT adoption behaviors, a rigorous measurement method is necessary.

[5] Source: National Bureau of Statistics (ed.), 2016: China Statistical Yearbook 2016, Beijing: China Statistics Press.

[6] Source: http://www.he.xinhuanet.com/xinwen/2018-08/10/c_1123249223.htm, August 10, 2018.

[7] Source: http://m.xinhuanet.com/ah/2018-09/21/c_1123462620.htm, September 21,2018.

[8] Source: http://www.js.chinanews.com/news/2018/0804/181773.html, August 4, 2018.

[9] Source: http://www.moa.gov.cn/xw/zwdt/201804/t20180409_6139792.htm, April 9, 2018.

5. Estimation results

5.1. Endogenous switching regression model

As shown in Table 3, the Wald χ^2 test significantly rejects the assumption that the decision equation and the outcome equation are independent from each other, and ρ_0 and ρ_1 are significantly nonzero at the 1% level. This indicates that there are unobservable factors that simultaneously affect family farms' welfare and GCT adoption.

From the estimation results of the decision equation, gender, education, risk preference, labor force size, financial status, media propaganda, agricultural technology department extensions and the distance to ATES significantly affect family farms' GCT adoption behavior.[10] However, age, frequency of communication with neighbors, cultivated land area and supervision of quality and safety of agricultural products do not have a significant impact, possibly for the following reasons. First, most of the family farmers in this survey sample are young people, with only slight differences in age. Second, in China, communication between rural neighbors is traditionally more of a type of chitchat (Xiao, 2017; Gao et al., 2017b). Third, family farms are motivated to adopt GCT when the cultivated land area exceeds a critical point, meaning that it has reached the standards for scale set by the local government and is relatively stable. Fourth, regardless of changes in the supervision of the quality and safety of agricultural products, family farms take profit-making as their fundamental purpose and adopt a business strategy that is “consumer-oriented, market-oriented, and future-oriented”. When the timing is appropriate, they will adopt GCT to save costs and increase revenues.

The results from the evaluation of the outcome equation show that regardless of whether the family farm adopts GCT, the characteristics of education, labor force size, financial status and agricultural technology department extensions have a significant positive impact on the level of welfare, while household head age has a significant negative impact. The reasons are as follows. First, as family farmers receive more education, their abilities in decision-making, the effective allocation of resources, and using relevant support policies will improve. As a result, family farms' welfare will increase. Second, the greater the labor force size, the less likely that family farms will miss farming seasons, with resulting effects on production and improved access to leisure time. Third, family farms with good financial status tend to have accessed a better socioeconomic status than other family farms, and they are likely to be more satisfied with their quality of life. Fourth, the increased efforts of agricultural technology departments help family farms master new technologies and access advanced management concepts, which undoubtedly have a positive effect on their economic condition. Fifth, as farmers' age increases, first, their learning and cognitive ability gradually declines, and their management capabilities decrease, causing the economic conditions of their family farms to decline. Second, they are more likely to experience health problems, which can lead to a decline in satisfaction with their quality of life. Gender, risk preference, frequency of communication with neighbors, cultivated land area, and supervision of quality and safety of agricultural products do not have a significant impact on the welfare of family farms, regardless of whether they adopted GCT.

[10] Existing studies have widely discussed the reasons these characteristics influence GCT adoption in detail; due to space limitations, this article does not repeat them.

Table 1
Descriptive statistics of variables.

Variable	Value criteria	Mean	Std. Dev
Outcome variable			
Welfare level	fuzzy comprehensive evaluation index	0.42	0.17
Treatment variable			
GCT adoption	1 = adopting; 0 = not adopting	0.31	0.46
High degree of adoption	1 = adopting ≥ 2 subtechnology types; 0 = otherwise	0.13	0.34
Low degree of adoption	1 = adopting only 1 subtechnology type; 0 = otherwise	0.18	0.39
Earlier adoption	1 = subjectively feels adopted early; 0 = otherwise	0.08	0.27
Later adoption	1 = subjectively feels adopted late; 0 = otherwise	0.23	0.42
Controlled variable			
Age	actual age in 2017 (year)	44.16	13.37
Gender	1 = male; 0 = female	0.86	0.35
Education	actual years of education completed	10.26	4.51
Risk preference	1 = strongly risk averse; 2 = risk averse; 3 = relatively risk averse; 4 = neutral; 5 = relatively risk loving; 6 = risk loving; 7 = strongly risk loving	3.31	1.19
Labor force size	sum of the number of family members who can provide labor plus the number of long-term employees	6.27	2.86
Cultivated land area	actual cultivated land area in 2017 (mu)	125.54	50.78
Financial status	1 = strongly scarce; 2 = scarce; 3 = relativeily scarce; 4 = neutral; 5 = relativeily abundant; 6 = abundant; 7 = strongly abundant	4.31	1.52
Frequency of communication with neighbors	1 = strongly low; 2 = low; 3 = relativeily low; 4 = neutral; 5 = relativeily high; 6 = high; 7 = strongly high	3.75	1.63
Media propaganda	1 = strongly low; 2 = low; 3 = relativeily low; 4 = neutral; 5 = relativeily high; 6 = high; 7 = strongly high	4.43	2.88
Agricultural technology departments' extension	1 = strongly low; 2 = low; 3 = relativeily low; 4 = neutral; 5 = relativeily high; 6 = high; 7 = strongly high	3.58	2.27
Supervision of quality and safety of agricultural products	1 = strongly low; 2 = low; 3 = relativeily low; 4 = neutral; 5 = relativeily high; 6 = high; 7 = strongly high	3.21	1.07
Identification variable			
ATES distance	distance (km) between a family farm and the nearest ATES	5.58	3.15

Table 2
Descriptive statistics of family farms' welfare indicators.

Variable	Value criteria	Adopters (n = 117)		Non-adopters (n = 258)		Difference
		Mean	Std. Dev	Mean	Std. Dev	
Economic conditions						
Net income from farming per mu	average value for the last three years (hundred yuan/mu)	6.12	3.07	5.43	2.69	0.69**
Social security						
Insurance	1 = insured; 0 = not insured	0.57	0.49	0.33	0.47	0.42***
Health and leisure						
Health status	1 = strongly poor; 2 = poor; 3 = relativeily poor; 4 = neutral; 5 = relativeily good; 6 = good; 7 = strongly good	5.88	2.87	4.51	1.97	1.37*
Leisure status	1 = strongly scarce; 2 = scarce; 3 = relativeily scarce; 4 = neutral; 5 = relativeily abundant; 6 = abundant; 7 = strongly abundant	3.91	2.82	2.80	2.07	1.11**
Psychological condition						
Satisfaction with quality of life	1 = strongly dissatisfied; 2 = dissatisfied; 3 = relativeily dissatisfied; 4 = neutral; 5 = relativeily satisfied; 6 = satisfied; 7 = strongly satisfied	4.48	1.72	3.26	1.50	1.22**

Note: The *P*-values are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance levels, respectively.

5.2. Average treatment effects of family farms' welfare

The results for the treatment effect of GCT adoption on family farms' welfare are presented in Table 4. The welfare treatment effect value of family farms that adopted GCT is 0.467; the welfare treatment effect value of family farms that did not adopt GCT is 0.379. If family farms that adopted GCT had not adopted this technology, their welfare treatment effect value would be 0.383; if family farms that did not adopt GCT had adopted this technology, the welfare treatment effect value would be 0.425. Hence, the average treatment effect (ATT) on the welfare of family farms that adopted GCT is 0.084, and the average treatment effect (ATU) on the welfare of family farms that did not adopt GCT is 0.046. If the family farms that adopted GCT renounced this technology, it would result in a welfare loss of 21.93%; if the family farms that did not adopt GCT adopted this technology, their welfare level would increase by 12.14%. Therefore, GCT helps to improve family farms' welfare.

5.3. Multinomial treatment effects model[11]

The estimation results of the MTEM are shown in Table 5. The estimation results show that, compared with family farms that did not adopt GCT, the welfare of family farms that adopted GCT to a high degree and to a low degree increased by 22.63% and 16.42%,

[11] Due to space limitations, the estimation results for the decision equation by multinomial treatment effects model are only discussed briefly.

Table 3
Estimates of the endogenous switching regression model.

Variable	Decision equation	Outcome equation	
		Adopters (n = 117)	Non-adopters (n = 248)
Age	−0.081 (0.134)	−0.008** (0.004)	−0.018*** (0.005)
Gender	0.058* (0.031)	0.037 (0.107)	0.028 (0.135)
Education	0.046** (0.022)	0.042** (0.019)	0.022*** (0.008)
Risk preference	0.103** (0.049)	0.042 (0.028)	0.027 (0.020)
Labor force size	−0.088* (0.052)	0.079* (0.043)	0.088** (0.038)
Cultivated land area	−0.187 (0.170)	0.045 (0.067)	0.038 (0.049)
Financial status	0.081** (0.035)	0.042*** (0.015)	0.038*** (0.012)
Frequency of communication with neighbors	0.093 (0.148)	0.104 (0.194)	0.132 (0.178)
Media propaganda	0.043** (0.019)	0.086 (0.060)	0.115 (0.095)
Agricultural technology department extensions	0.088* (0.049)	0.088** (0.043)	0.034* (0.018)
Supervision of quality and safety of agricultural products	0.027 (0.074)	0.056 (0.053)	0.067 (0.049)
ATES distance	−0.326*** (0.126)	–	–
Constant	−3.235*** (1.232)	0.377*** (0.129)	0.336*** (0.130)
σ_{u0}, σ_{u1}	–	0.881** (0.362)	0.375* (0.185)
ρ_0, ρ_1	–	−0.897*** (0.141)	−0.935*** (0.244)
Wald χ^2	–	23.551***	31.792***
Log likelihood	−794.307	–	−785.344
F-statistics	–	639.472***	724.162***
No. of observations	375	375	

Note: The *P*-values are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance levels, respectively.
The bracketed values are standard errors.

Table 4
Average treatment effects on family farms' welfare.

Outcome variable	Family farm type and treatment effect	Decision type		ATT/ATU	t-statistics	ATT/ATU in %
		Adopt GCT	Not adopt			
Welfare level	GCT adopters (ATT)	0.467 (0.134)	0.383 (0.237)	0.084***	8.326	21.932
	GCT non-adopters (ATU)	0.425 (0.125)	0.379 (0.116)	0.046***	8.973	12.137

Note: The *P*-values are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance levels, respectively.
The bracketed values are standard errors.

Table 5
Estimates of multinomial treatment effects model.

Variable	Model 1 (adoption degree)	Variable	Model 2 (adoption timing)
High degree of adoption	0.204*** (0.071)	Earlier adoption	0.057*** (0.021)
Low degree of adoption	0.152** (0.063)	Later adoption	0.073** (0.034)
Age	−0.004** (0.002)	Age	−0.007* (0.004)
Gender	0.028 (0.035)	Gender	0.046* (0.039)
Education	0.040*** (0.015)	Education	0.037*** (0.013)
Risk preference	0.013 (0.016)	Risk preference	0.115 (0.083)
Labor force size	−0.046** (0.027)	Labor force size	−0.052** (0.025)
Financial status	0.048** (0.023)	Financial status	0.073 (0.219)
Frequency of communication with neighbors	0.216 (0.313)	Frequency of communication with neighbors	0.012 (0.008)
Media propaganda	0.021 (0.031)	Media propaganda	0.018 (0.046)
Agricultural technology department extensions	0.049** (0.023)	Agricultural technology department extension	0.021** (0.009)
Supervision of quality and safety of agricultural products	0.032 (0.217)	Supervision of quality and safety of agricultural products	0.041 (0.055)
Constant	3.026*** (0.943)	Constant	4.071*** (0.193)
λ (high degree of adoption)	0.920*** (0.199)	λ (earlier adoption)	0.591** (0.262)
λ (low degree of adoption)	0.787** (0.377)	λ (later adoption)	0.328*** (0.114)
No. of observations	375	No. of observations	375

Note: The *P*-values are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance levels, respectively.
The bracketed values are standard errors.

respectively, which means that the degree of GCT adoption will lead to different levels of welfare; i.e., a high degree of adoption leads to a greater welfare effect than a low degree of adoption.

In addition, compared with family farms that did not adopt GCT, the welfare of family farms that adopted GCT earlier or later was increased by 5.87% and 7.57%, respectively, which means that different GCT adoption timing results in different levels of welfare. This may be because family farms that adopted GCT later have more opportunities to learn from the failures of family farms that adopted GCT earlier, thus greatly circumventing the operational risk[12] of adopting GCT.

6. Conclusions

In this paper, we use an ESRM and a MTEM to discuss the impact of the adoption and non-adoption of GCT on family farms' welfare, and we estimate the welfare effects of the degree and timing of adoption. The estimation results from the ESRM shows that GCT helps to improve the welfare of family farms. The estimation results from the MTEM show that the welfare effect for family farms with a higher adoption level is greater than that for family farms with a lower adoption level of GCT, and the welfare level of family farms that adopted GCT later is greater than that of family farms that adopted GCT earlier.

The main research conclusions of this paper provide theoretical support for China's extension of GCT. The paper also provides the following policy implications.

First, the GCT extension policy system should be more broadly established and improved. By strengthening publicity, improving the financing environment, promoting training, consolidating efforts to re-educate family farmers, and intensifying the construction of grassroots technology extension institutes, a sound GCT extension policy system could be established. This would improve the internal and external conditions for adoption and the external environment of family farms and eradicate obstacles to adopting GCT.

Second, family farms should be guided to deepen their degree of GCT adoption. Giving family farms with a high degree of GCT adoption more subsidies than family farms with a low degree of adoption would increase the incentive to deepen their GCT adoption. Making full use of rural grassroots organizations, supplemented by new media platforms such as Weibo and WeChat, would fully publicize the effects of a high adoption degree of GCT on family farms' welfare and establish the understanding that “high is better than low” among farmers.

Third, policies should be more targeted towards family farms that have earlier adoption timing. Policy makers can improve the sense of well-being of family farms that adopted GCT earlier by publicly commending them. In terms of formulating policies on credit, insurance, education and training, priority should be given to family farms that adopt GCT earlier to minimize their potential operating risks.

Acknowledgements

This work was supported by the National Natural Science Foundation of China [grant number: 71803096], the humanity and Social Science of Ministry of Education of China [grant number: 18YJA790024], and the Shandong Province Natural Science Foundation of China [grant number: ZR2018MG009].

[12] Operational risk mainly includes the following issues. First, family farms adopt GCT as a productive investment activity, but there is uncertainty regarding the net income of the family farm caused by asymmetric price information in the agricultural product market. Second, because GCT is a knowledge-intensive technology, it has higher requirements for technology adopters, which leads to a risk from the improper use of GCT.

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