



Towards more efficient low-carbon agricultural technology extension in China: identifying lead smallholder farmers and their behavioral determinants

Kai Li¹ · Qi Li¹

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Abstract

In the transition to low-carbon agriculture, smallholder farmers face more constraints. Identifying lead smallholder farmers and leveraging their peer effects can accelerate low-carbon agricultural technology extension among smallholder farmers. Based on survey data from 643 rice farmers in Zhejiang Province, China, this study constructs a finite mixture model (FMM) to identify lead smallholder farmers and then uses a quantile regression model (QRM) to explore their behavioral determinants. The main conclusions are as follows. First, despite the homogeneity in the production mode and resource constraints, lead smallholder farmers are younger and more open to risk, and they have higher educational levels and more family laborers. Second, a higher use efficiency of heterogeneous information is the key to differentiating lead smallholder farmers from other smallholder farmers. Third, green agricultural producer services can effectively alleviate resource constraints and contribute to the low-carbon transition of all smallholder farmers. These results can help redesign targeted extension policies to incentivize lead smallholder farmers.

Keywords Low-carbon agriculture · Lead smallholder farmers · Social network · Technology extension · Finite mixture model · Quantile regression model

Introduction

As an important part of the ecosystem, agriculture is not only a key supplier of ecological products but also a major source of greenhouse gases (IPCC 2019). The overuse of chemical inputs has led to a surge in agricultural N₂O emissions as well as a series of adverse effects on ecosystem sustainability and food safety (Snyder et al. 2009; Gómez et al. 2013; Zeng et al. 2014; Yin et al. 2018). Thus, there is an urgent need to reduce chemical inputs and develop low-carbon agriculture to address declining ecosystem quality and continuing climate change.

Reducing chemical inputs is a vital but challenging task for smallholder farmers (Andersson and D'Souza 2014; Zeweld et al. 2017; Jin et al. 2021), especially in developing

countries where smallholder farms are still widespread. Approximately 3.4 billion people worldwide live in the rural areas of developing countries, and most of them depend on smallholder farms. Small family farms (i.e., those of less than 2 ha) account for 85% of all farms worldwide (IFAD). In China, data from the third national agricultural census showed that the number of smallholder farmers accounted for approximately 98% of the total number of agricultural households and that 71.4% of cultivated land was still managed by smallholder farmers. At the same time, the overuse of chemical inputs by smallholder farmers is more serious. Wu et al. (2018) found that farm size is significantly and negatively correlated with chemical fertilizer use per hectare, both in China and in 74 other countries across five continents. Most importantly, smallholder farmers' transition to low-carbon agriculture faces more constraints. First, low-carbon agricultural technologies have higher requirements for capital, labor, and knowledge, many of which have scale thresholds (Wu et al. 2018). Second, due to deficient resources and limited access to technical information (Zhou 2017; Han 2019; Llewellyn and Brown 2020), smallholder farmers are more cautious with regard to low-carbon

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✉ Qi Li
liqi@qfnu.edu.cn

¹ School of Economics, Qufu Normal University, Room 720, 80 Yantai North Road, Rizhao 276826, China

agricultural technologies. Due to these problems, smallholder farmers are unwilling or unable to adopt new low-carbon technologies.

As an effective complement to public extension, peer effects and social learning among smallholder farmers are indispensable for solving the dilemma of these farmers' low-carbon transition. In developing countries, traditional public extension usually cannot cover large parts of the intended population (de Janvry et al. 2016; Sun 2021). Therefore, targeting progressive farmers (Maertens 2017), seeding farmers (Banerjee et al. 2019) or disseminating farmers (Shikuku et al. 2019) to leverage their peer effects and activate social learning has attracted the attention of policymakers and scholars. In traditional work, policymakers usually target farmers who are better off or who are central in social networks (Kim et al. 2015; Beaman et al. 2021). However, such farmers may not be representative of all farmers, and their experiences may be of limited value to others, especially smallholder farmers (e.g., Munshi 2004; Conley and Udry 2010; BenYishay and Mobarak 2019). Moreover, smallholder farmers have a higher technology adoption threshold, and they rely more on the experiences of their peers (Ward and Pede 2015; Beaman et al. 2021). Consequently, identifying lead smallholder farmers and leveraging their peer effects will be more meaningful for the low-carbon transition of smallholder farmers.

However, we still know very little about who lead smallholder farmers in the low-carbon transition are and what factors differentiate them from other smallholder farmers. China offers a unique setting to identify lead smallholder farmers and their behavioral determinants. In 2016, China implemented the "Action to Achieve Zero Growth in Chemical Fertilizer Use by 2020" and the "Action to Achieve Zero Growth in Pesticide Use by 2020". More than 3 million large-scale farmers, technicians from productive service organizations and seed farmers were trained every year over the past 5 years. Despite that, smallholder farmers still struggle to reduce their chemical inputs (Gao et al. 2019; Liu 2020; Zhang 2020), and differences in the low-carbon transition of smallholder farmers are beginning to emerge. Based on survey data from 643 rice farmers in Zhejiang Province, China, this study first presents a production function through a finite mixture model (FMM) to differentiate smallholder farmers in the low-carbon transition and to identify lead smallholder farmers. On this basis, this study uses a quantile regression model (QRM) to explore the constraints faced by lead smallholder farmers in their transition. In this way, this study provides insights for redesigning extension policies for low-carbon agricultural technologies for smallholder farmers in the future.

This study makes three main contributions. First, unlike previous studies that target the seeding farmers or progressive farmers among all farmers, this study attempts to

distinguish lead farmers from smallholder farmers because the latter face more challenges in the low-carbon transition and rely more on the experiences of their peers. Second, considering the diversity in the reduction in chemical inputs and the differences in resource endowment requirements, smallholder farmers may show preferences for technologies that match their resource endowments. Thus, the traditional criterion, i.e., involving the use of the initial adoption time of a certain technology, is not applicable in this situation. A more comprehensive criterion that includes the utilization rate of chemical fertilizer and the adoption rate of multiple low-carbon agricultural technologies is used to identify lead smallholder farmers. Third, this article explores the constraints faced by lead smallholder farmers and provides a new perspective from which to understand the ambiguous relationship between social learning and technology adoption. These contributions allow us to redesign targeted policies for providing incentives to lead smallholder farmers and promoting the low-carbon transition of all smallholder farmers.

Theoretical framework

Peer effects and the role of lead smallholder farmers in the low-carbon transition

Rogers (2003) argued that "the heart of the diffusion process is the imitation by potential adopters of their near peers' experiences". Limited by household resources and access to technology information, smallholder farmers usually lag behind in the diffusion of agricultural technology. According to the theory of innovation diffusion, smallholder farmers can be classified as the late majority or laggards. They may adopt a new technology only after most, if not all, of the surrounding farmers have adopted it. In other words, they have higher adoption thresholds (a larger number of other individuals who may influence an individual's decision regarding technology adoption). Considering that innovators or early adopters account for only a very limited proportion of all farmers, their experience is far from sufficient. Therefore, among smallholder farmers, the experience of relatively early adopters, namely, lead smallholder farmers whom we look for, is indispensable for smallholder farmers.

Moreover, the experience of lead smallholder farmers is more valuable for smallholder farmers. Peer effects can be divided into the information effect, experience effect and externality effect (Xiong and Xiao 2021). The information effect refers to the general information conveyed through social networks (Banerjee et al. 2013); the experience effect refers to the more detailed, accurate, and local experiences of earlier adopters (Conley and Udry 2010); and the externality effect refers to the pressure from peers' technology adoption

(Katz et al. 1986). Among these three kinds of peer effects, only the experience effect can induce large-scale innovation diffusion (Xiong and Xiao 2021). The role of the experience effect is more prominent mainly because these experiences come from similar adopters, the same smallholder production or the same agricultural environment; thus, these experiences are more informative and practicable. Therefore, the experiences of lead smallholder farmers are indispensable and more valuable for smallholder farmers in the low-carbon transition.

Thus, identifying lead smallholder farmers and making use of their peer effects are crucial for accelerating the low-carbon production transition of smallholder farmers. It is also necessary to explore the constraints faced by lead smallholder farmers to promote their transition as rapidly as possible.

Criterion for identifying lead smallholder farmers in the low-carbon transition

Before we define lead smallholder farmers, we first need to define smallholder farmers. According to the official statistical standard from the third national agricultural census in 2016, if a farmer's cultivated land area reaches 50 mu (1 mu = 0.067 ha) or more in a double-crop rice cultivation region, he/she will be considered a large-scale farmer; otherwise, he/she will be considered a smallholder farmer.

From the perspective of innovation diffusion, the main criterion for grouping adopters is the length of their innovation decision period or the time sequence of adopting the innovation. However, due to limited resources, smallholder farmers adopt only those technologies that match their resource endowments and ignore other technologies (Just and Zilberman 1988; Grabowski and Kerr 2014; Zheng et al. 2018). We define that as “resource-biased technology adoption”. Given this situation, the traditional criterion is no longer suitable. Therefore, a more comprehensive criterion is needed to rectify the biased selection of smallholder farmers.

This study sets two indicators to identify lead smallholder farmers: one concerns the result of chemical fertilizer reduction, and the other concerns the adoption of divisible low-carbon agricultural technologies. First, this study uses the utilization rate of chemical fertilizer as a proxy variable to measure the result of chemical fertilizer reduction. Different from previous studies, in this paper, the fertilizer utilization rate is estimated by the rice yield per 50 kg of chemical fertilizer. In such cases, the greater the rice yield is with the same chemical fertilizer inputs, the higher the fertilizer utilization rate and the more successful the low-carbon transition. Second, this study chooses four divisible low-carbon technologies (Szmedra et al. 1990; Dimara and Skuras 2003; Khaledi et al. 2010) to measure the differences in low-carbon

agricultural technology adoption. These four technologies are organic fertilization, stalk shredding and plowing, integrated pest management (IPM), and slow-release fertilizer. All these technologies are promoted as a chemical fertilizer reduction package: each technology has unique functions in terms of reducing chemical fertilizer and different requirements for smallholder farmers' resource endowments. Therefore, they can be adopted independently. Moreover, these technologies are complementary in reducing chemical fertilizer, and therefore, they can also be adopted integrally. The higher the number of technologies adopted by a farmer is, the more obvious his/her preference for new technologies, the stronger his/her inner innovation spirit, and the greater the likelihood that he/she will be treated as a lead smallholder farmer.

Behavioral determinants of lead smallholder farmers

According to the theory of innovation diffusion, the attributes of innovation, the personal characteristics of the decision-maker, and communication channels are the main determinants in grouping adopters. Because we set a variety of technologies that can be selected independently, the attributes of technologies can be considered homogeneous for the sampled farmers. Therefore, in this paper, the behavioral determinants are mainly derived from the personal, economic, and social characteristics of farmers, communication behaviors, and communication channels. The specific influencing factors mainly include the following:

Personal, economic, and social characteristics of farmers. Earlier adopters usually have a higher level of literacy, a higher social status, and higher social mobility, and they are usually more open to risk taking. They also have enough financial resources to accept risk (Rogers 2003). Therefore, this paper selects educational level, the age of the head of household, and risk preferences to measure farmers' personal characteristics, and it uses the land area and the degree of part-time employment of farmers to represent their economic and social status.

Communication behavior and communication channels. According to the theory of innovation diffusion, earlier adopters have a wider range of social relationships and have more access to external and general information than late adopters. External and general information can change adopters' perceptions and have a greater impact on early adopters (Rogers 2003; Chen et al. 2019). Additionally, interpersonal channels (social networks, especially peer interactions) can change adopters' attitudes through two-way communication and persuasion, and they can have a more profound impact on late adopters and laggards. This paper chooses government technical training to measure the difference in access to external and general information. Considering that social

networks have a “stronger and more direct impact” on smallholder farmers (Holloway et al. 2002; Krishnan and Patnam 2014), we select social networks to represent the difference in interpersonal channels. The effect of social networks is closely related to the size of social networks and the position of individuals in social networks (Bandiera and Rasul 2006; Zhu 2016; Yin et al. 2019). Therefore, this paper measures the social network size and the social network centrality of smallholder farmers using the number of villagers with whom they frequently keep in touch and whether they have served as village cadres, respectively.

Data and methods

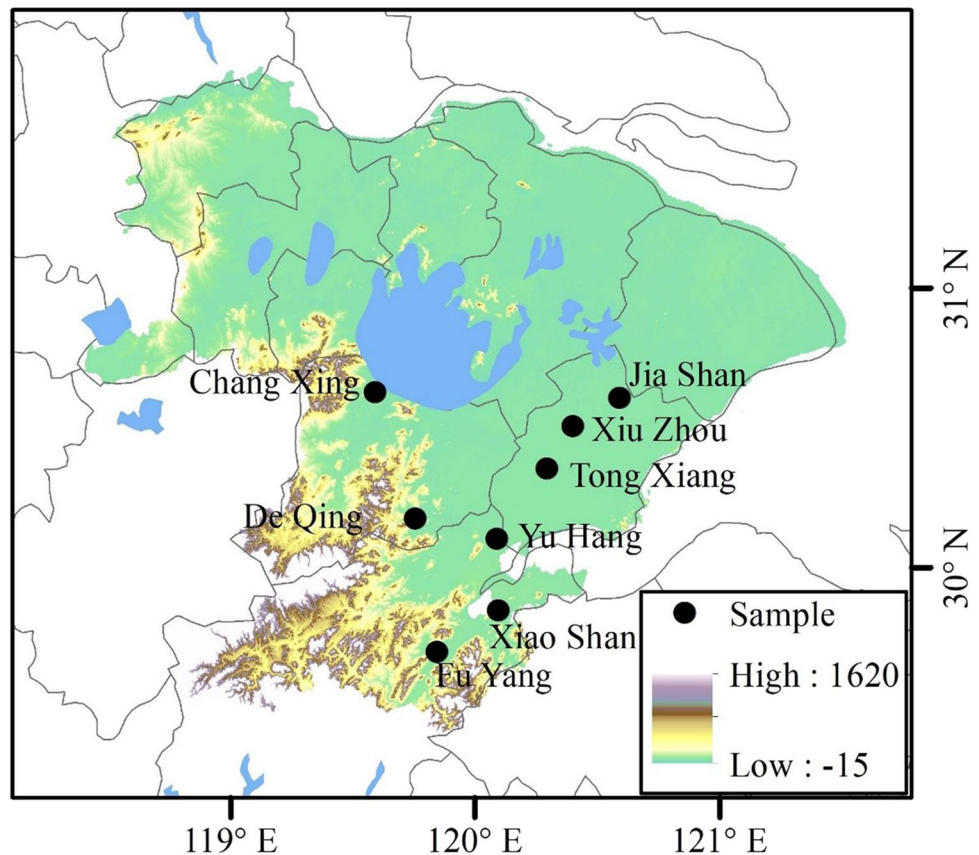
Study region

Rice cultivation is an important source of greenhouse gases such as methane and N_2O . The region for single- and double-crop rice in Central China accounts for approximately 59% of the country’s total rice cultivation area. As a typical rice production area for single- and double-crop rice in Central China, the Hangjiahu Plain is located in the southern Taihu Basin in the northern part of Zhejiang Province. It is the largest plain in Zhejiang Province and

has a total area of approximately 7620 km², covering all of Jiaxing, most of Huzhou and the north-eastern part of Hangzhou (Fig. 1).

We select the Hangjiahu Plain as the study region for two main reasons. First, Zhejiang is a pilot area for low-carbon agriculture in China, with sufficient sample smallholder farmers transitioning to low-carbon agriculture. As early as 2013, Zhejiang Province started the “water resource treatment” project and the “action to reduce chemical fertilizer” to promote the green and low-carbon transition of agriculture. An almost 10-year low-carbon technology diffusion period provides a complete and more accurate picture of the differences in adoption among smallholder farmers. Second, smallholder production is still dominant in the Hangjiahu Plain. Zhejiang Province is one of the provinces with the least arable land per capita in China. The third national land resource survey in 2019 revealed that the arable land per capita in Zhejiang Province was only 0.3 mu, much lower than the national average (1.36 mu). The average proportion of smallholder farmers in Jiaxing, Huzhou, and Hangzhou is 98%, basically the same as the nationwide proportion (98.08%). Therefore, the samples in the Hangjiahu Plain can reflect the differentiation of smallholder farmers in the low-carbon transition and to facilitate the identification of lead smallholder farmers.

Fig. 1 Study region



Data collection

A total of 643 smallholder farmers from eight counties were selected through multistage cluster sampling in 2020. First, out of 11 major grain-producing counties in Zhejiang, 6 counties were randomly selected in the Hangjiahu Plain (including 1 county in Hangzhou, 3 counties in Jiaxing, and 2 counties in Huzhou) and 2 counties in surrounding areas (Fuyang and Xiaoshan in Hangzhou). Second, in each selected county, 1 town with provincial green agricultural demonstration projects and 1–2 towns without demonstration projects were selected from the list of the main rice-growing villages provided by the county agricultural bureau. Third, approximately 15–20 households were randomly selected from the list of households provided by the village cadre. A total of 824 questionnaires were collected, including 643 questionnaires for smallholder farmers with land scales less than 50 mu.

The questionnaire covered five main aspects: the personal, economic, and social characteristics of farmers; the social networks of farmers; the costs and benefits of rice planting; the adoption of low-carbon agricultural technologies; and agricultural producer services and government support. The investigators were mainly undergraduates from Zhejiang University, Huzhou Normal University, and Jiaxing College. Before the survey, the questionnaire designer provided special training to the investigators to ensure that each investigator understood the meaning and purpose of each question.

Methods

Finite mixture model

We use an FMM to estimate the heterogeneity of smallholder farmers in the low-carbon transition. As an application of latent class regression models, FMMs have two unique features. First, the observed conditional distribution of the production function in our research is assumed to be a mixture of two or more distributions with different means and variances, and the parameters of the production function are allowed to differ across groups (Owen et al. 2009). This feature can help us target lead small farmers and capture the differences between them and other smallholder farmers. Second, the number of groups within smallholder farmers and which group one sample farmer belongs to are endogenously determined, and posterior probability can be calculated (Kasahara and Shimotsu 2009; Konte 2013). This feature facilitates the explanation of the sources of systematic heterogeneity by the QRM.

We first construct a production function. The dependent variable is the rice yield per 50 kg of chemical fertilizer, and the independent variables are other inputs for rice production, including the seedling cost, pesticide cost, machinery cost, labor, and land input; the adoptions of the four divisible technologies are covariates. Notably, unlike the general production function, which uses the total yield or yield per mu as the output, the rice yield per 50 kg of chemical fertilizer is used as the output variable to directly show the difference in the utilization efficiency of chemical fertilizer. A higher output means a larger rice yield per 50 kg of chemical fertilizer and, thus, higher chemical fertilizer use efficiency.

Specifically, we assume that the production function can be classified into K discrete classes. That is, smallholder farmers can be divided into K groups based on the difference in the low-carbon transition. The basic form of the FMM is as follows:

$$f(Y|X, \theta) = \sum_{k=1}^K \pi_k f((Y|X, \theta_k)) = \pi_1 f_1(X) + \pi_2 f_2(X) + \dots + \pi_k f_k(X) \tag{1}$$

where $f((Y|X, \theta_k))$ is the conditional probability density of sample Y falling into latent class K due to unobservable heterogeneity; X is a vector of the independent variables (all kinds of inputs); θ_k is a parameter to be estimated; and π_k is the mixing ratio, which is also known as the weight corresponding to each subdensity $f_k(X)$ and satisfies $\sum \pi_k = 1$.

The probability distribution, which reflects the input–output relationship, can be explained by the covariates (the adoptions of the four divisible technologies). For example, if the sample can be divided into two classes, then its distribution function can be expressed as follows:

$$f(Y|X, \theta) = \pi_H f_H(X) + \pi_L f_L(X) \tag{2}$$

$$P(j|X, Y) = \frac{\pi_j f_j(Y|X, \theta_j)}{\pi_H f_H(Y|X, \theta_H) + \pi_L f_L(Y|X, \theta_L)} \tag{3}$$

The estimated posterior probability of each sample farmer falling into the j th class, $j = (I, K)$, is calculated by Eq. (3), and P_I and P_K are the posterior probabilities of the sample falling into two latent classes, I and K , respectively.

Quantile regression model

To explore the behavioral determinants of lead smallholder farmers in the low-carbon transition, a QRM is established. The probability that a farmer is a lead smallholder farmer (i.e., the probability of the sampled farmers falling into the lead smallholder farmers group, which is estimated using Eq. (3)) is the dependent variable. In the QRM, the independent variables mainly include the personal, economic

and social characteristics of a farmer (attitude towards risk, educational level, age, land area, and part-time employment), communication behaviors and communication channels (number of technical training sessions received by the interviewed farmer per year and social networks). In addition, drawing on existing studies on resource-biased technology selection, we introduce labor quantity and whether producer service organizations exist as control variables.

The advantages of the QRM are that, first, it describes the overall conditional distribution of the independent variables and demonstrates the differences in influencing factors at different quantiles (Koenker and Hallock 2001). By comparing the differences in the influencing factors of lead smallholder farmers and laggards, we can explore the key reasons for this differentiation in the low-carbon transition and what drives lead smallholder farmers. In addition, QRMs are less susceptible to extreme values and lead to more robust regression results than do least squares methods (Yu et al. 2003; Koenker 2017). The QRM for the above differentiation in the low-carbon transition is as follows:

$$Y_{i,q} = \sum_{j=1}^n \alpha_j X_{ij,q} + \sum_{k=1}^n \beta_k Z_{ik,q} + \varepsilon_{i,q} \quad (4)$$

where $Y_{i,q}$ is the probability of the i th farmer falling into the lead smallholder group; q is the quantile; $X_{ij,q}$ is the personal, economic and social characteristic variables and communication behavior and communication channel variables; $Z_{ik,q}$ is a series of control variables; $\alpha_{j,q}$ and $\beta_{k,q}$ are

the regression coefficients of the corresponding variables at quantile q ; and $\varepsilon_{i,q}$ is the random error term at quantile q .

Descriptive statistics

As the descriptive statistical analysis shows (Table 1), the mean rice yield per 50 kg of chemical fertilizer is 766.9 kg, but the standard deviation reaches 429.76 kg, indicating substantial variation in the sample. Among the four low-carbon agricultural technologies, the mean amount of organic fertilizer used (including commercial and self-cultivated organic fertilizer) is approximately 233.3 kg, and the mean adoption rates of stalk shredding and plowing, IPM, and slow-release fertilizer are 65.94%, 44.42%, and 26.91%, respectively.

The sample smallholder farmers can be characterized by a low educational level, age, and risk aversion. There are approximately two laborers with a high level of part-time employment, and the proportion of nonfarm income in household income exceeds 60%. Constrained by family resources, the mean land area is only 6.47 mu, which is far less than 50 mu and very scattered. Farmers have received fewer than two training sessions on eco-friendly technology, indicating that smallholder farmers face limitations in acquiring external technological knowledge. In terms of social networks (Table 2), the number of villagers with whom smallholder farmers maintain regular contact is approximately seven, and 8% of the farmers have served as village cadres. Moreover, the coverage rate of green producer service organizations exceeds 70%.

Table 1 Variables in the FMM and the descriptive statistics

	Name	Definition	Mean	St. Dev
Dependent variable	Rice yield	Rice yield per 50 kg of chemical fertilizer (kg)	766.8967	429.7609
Independent variables	Seedling cost	Seedling input converted by yield (yuan) ^a	3.0012	2.6027
	Pesticide cost	Pesticide input converted by yield (yuan)	103.9150	66.3561
	Machinery cost	Machinery input converted by yield (yuan) ^b	150.4736	138.2094
	Labor input	Labor input converted by yield (days)	3.9847	3.8924
	Land input	Land input converted by yield (mu)	1.5714	0.7298
Covariates	Organic fertilization	Amount of organic fertilizer converted by yield (kg)	233.3026	217.6446
	Stalk shredding and plowing	Whether it is adopted: yes = 1, no = 0	0.6594	0.4743
	IPM	Whether it is adopted: yes = 1, no = 0	0.4442	0.4576
	Slow-release fertilizer	Whether it is adopted: yes = 1, no = 0	0.2691	0.4438

(a) For example, the chemical fertilizer input is 40 kg per mu; the seedling cost, pesticide cost, machinery cost, labour input, and land input are 8 yuan, 40 yuan, 60 yuan, 12 days, and 1 mu, respectively; and the yield is 500 kg. Thus, the rice yield per 50 kg of chemical fertilizer is $500 \times 50 / 40 = 625$ kg, the seedling cost converted by yield is $8 \times 625 / 500 = 10$ yuan, the pesticide cost converted by yield is $40 \times 625 / 500 = 50$ yuan, the machinery cost converted by yield is $60 \times 625 / 500 = 75$ yuan, the labour input converted by yield is $12 \times 625 / 500 = 15$ days, and the land input converted by yield is $1 \times 625 / 500 = 1.25$ mu

(b) Among the input variables, the machinery input is 0 since smallholder farmers are likely to rely entirely on their own labour for production operations. Referring to Battese's method of adding dummy variables (Battese, 2010), we set the machinery input to 0 to ensure the unbiased estimation of the production function

Table 2 Variables in the QRM and the descriptive statistics

	Variable	Definition	Mean	St. Dev
Dependent variable	Probability that farmers are lead farmers	Probability that farmers are lead farmers (%)	0.3343	0.3711
Independent variables	Risk attitude	Risk preference = 1; risk neutral/risk aversion = 0	0.3421	0.4748
	Educational level	Educational level of the head of household: primary school or below = 1; junior school = 2; high school = 3; above high school = 4	1.9238	0.8440
	Age	Age of the head of household (years)	51.6791	8.9015
	Land area	Operational land area of rice (mu)	6.4688	10.9897
	Part-time employment	Proportion of nonfarm income of total income (%)	60.6540	26.4389
	Technical training	Number of technical trainings received by the interviewed farmers per year	1.9907	1.0937
	Social network size	Number of villagers who frequently keep in touch (people)	7.0467	3.9254
	Social network centrality	Whether acquaintances have served as village cadres: yes = 1; no = 0	0.0793	0.2704
Control variables	Labor quantity	Number of family laborers (people)	2.1415	0.9223
	Producer services	Whether there are producer service organizations: yes = 1; no = 0	0.7045	0.4566

Results

Results of identifying lead smallholder farmers

First, the optimal number of groups is determined based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC):

$$AIC = 2k - 2\ln(L) \tag{5}$$

$$BIC = k\ln(n) - 2\ln(L) \tag{6}$$

where *k* is the number of model parameters, *L* is the likelihood function, and *n* in Eq. (6) is the sample size.

The results show that minimum values of both the AIC and BIC are obtained when the number of classes is 3 (Table 3), indicating that the sampled farmers in the green transition can be divided into three classes based on unobservable heterogeneity.

Based on the posterior probabilities and estimated marginal mean of the latent classes (Table 4), the probabilities of a sample falling into subclasses 1, 2, and 3 are 16.17%, 44.98%, and 38.85%, respectively. There are significant differences in the utilization efficiency of chemical fertilizer among the three groups, with mean yields of 681.24 kg, 625.03 kg, and 891.01 kg for subclasses 1, 2, and 3, respectively. Regarding the differences in the adoption of

low-carbon agricultural technologies, the analysis of variance (Table 5) shows significant differences in all technologies, except for stalk shredding and plowing. Additionally, the Bonferroni test (Table 6) shows that the adoption rates of organic fertilization, IPM, and slow-release fertilizer in subclass 3 are significantly higher than those in the other two subclasses and that the adoption rate of IPM is significantly higher in subclass 2 than in subclass 1.

With a higher utilization efficiency of chemical fertilizer and a higher adoption rate of low-carbon agricultural technologies, farmers in subclass 3 are the lead smallholder farmers in low-carbon agriculture. Farmers in subclasses 1 and 2 correspond to “survival-oriented smallholder farmers” and “production-oriented smallholder farmers”, respectively (Zhang 2020). Although the farmers in subclass 1 have a higher utilization efficiency of chemical fertilizer than do those in subclass 2, these farmers have the lowest adoption rate of low-carbon technologies, indicating that they intentionally control chemical fertilizer inputs and increase free family labor input to reduce their input costs. This finding is in line with the characteristics of survival-oriented farmers,

Table 4 Posterior probabilities of samples falling into the latent classes and the estimated marginal means

Classes	Posterior probabilities of samples falling into the latent classes		Estimated marginal means of the latent classes		
	Margin	Delta method Std. Err	Margin	Delta method Std. Err	Z value
Subclass 1	0.1617	0.0297	681.2391	8.9447	76.1600
Subclass 2	0.4498	0.0465	625.0278	17.8897	34.9400
Subclass 3	0.3885	0.0420	891.0142	20.9521	42.5300

Table 3 Results of the AIC and BIC tests

Classes	DF	AIC	BIC
1	9	8,591.389	8,631.213
2	23	8,444.714	8,551.991
3	31	8,414.82	8,546.486

whose primary goal is to reduce their cost of living. In contrast, farmers in subclass 2 have higher chemical fertilizer inputs and adopt IPM to reduce labor inputs, ensuring that enough labor can be transferred to non-agricultural businesses with higher returns and maximizing total household income. In such cases, the farmers in subclass 2 exhibit the characteristics of production-oriented farmers.

In terms of personal characteristics, lead smallholder farmers are younger and more open to risk, and they also have higher educational levels and more family laborers. As shown in Table 7, there are significant differences in personal, economic, and social characteristics among the three groups of smallholder farmers, but there are no significant differences in communication behavior and communication channels. Compared with the other two groups, lead smallholder farmers are younger and better educated, which empowers them and makes them more capable of learning new technologies. Lead smallholder farmers are more open to risk, and they are more willing to embrace new low-carbon technologies. Meanwhile, more laborers help to ease the constraints imposed by labor-intensive technology. However, there is no significant difference in the land area, part-time

employment, social networks (size and centrality), and technical training among the three groups, indicating that the sample smallholders are homogeneous in their production mode and communication channels.

Behavioral determinants of lead smallholder farmers

After combining the posterior probability and probability distribution of the sampled lead farmers, we select the 25% (posterior probability is 5.5%, referred to as “laggards”) and 75% (posterior probability is 80.2%, referred to as “lead smallholder farmers”) quantiles to identify the factors driving lead smallholder farmers. To test the robustness of the estimation results, we add the 50% quantile (posterior probability is 18.49%) for comparison.

The quantile regression results show that social network size, technical training, labor quantity, and producer services have a significant influence on lead smallholder farmers (Q75 in Table 8). However, only social network size and producer services have a significant influence on both quantiles.

Table 5 Adoption of low-carbon agricultural technologies by the three groups

	Subclass 1		Subclass 2		Subclass 3		St. Dev	
	Samples	Mean	Samples	Mean	Samples	Mean	F value	P value
Organic fertilizer	104	294.8481	289	436.3551	250	620.8015	6.60	0.0015***
Stalk shredding and plowing	104	0.6216	289	0.6703	250	0.6712	0.61	0.5438
IPM	104	0.1149	289	0.3743	250	0.7548	128.54	0.0000***
Slow-release fertilizer	104	0.0608	289	0.1341	250	0.58	111.20	0.0000***

***, **, and * Significance at the 1%, 5%, and 10% levels, respectively

Table 6 Bonferroni test of technology adoption

	Organic fertilizer		Stalk shredding and plowing		IPM		Slow-release fertilizer	
	Difference	Sig	Difference	Sig	Difference	Sig	Difference	Sig
Subclasses 1 and 2	222.3640	0.3240	0.0487	0.9440	0.2594	0.0000***	0.0732	0.1830
Subclasses 1 and 3	512.2030	0.0010***	0.0496	0.9790	0.6399	0.0000***	0.5191	0.0000***
Subclasses 2 and 3	289.8390	0.0550*	0.0009	1.0000	0.3805	0.0000***	0.4459	0.0000***

***, **, * Significance at the 1%, 5% and 10% levels, respectively

Table 7 Bonferroni test of the characteristics among the three groups

		Risk attitude	Educational level	Age	Labor quantity
		Difference	Difference	Difference	Difference
Lead smallholder farmers	Survival-oriented smallholder farmers	0.122*	0.278*	−2.32*	0.334*
	Production-oriented smallholder farmers	0.112*	0.199*	−1.56	0.214*

***, **, and * Significance at the 1%, 5%, and 10% levels, respectively

Table 8 Quantile regression results

Variables	Laggards (Q25)			Q50			Lead farmers (Q75)		
	Coefficient	St. Dev	T value	Coefficient	St. Dev	T value	Coefficient	St. Dev	T value
Risk attitude	0.0170*	0.0090	1.9000	0.1137**	0.0488	2.33	0.1185	0.0730	1.6200
Educational level	0.0042	0.0048	0.8800	0.056	0.02	2.76	0.0559	0.0393	1.4200
Age	−0.0003	0.0004	−0.6900	−0.0029	0.0025	−1.18	−0.0043	0.0039	−1.1000
Land area	0.0005	0.0015	0.3100	0.0037*	0.0019	1.96	0.0010	0.0021	0.4600
Part-time employment	0.0002*	0.0001	1.6900	0.001	0.0007	1.35	0.0013	0.0012	1.0200
Technical training	0.0051	0.0033	1.5300	0.0288	0.0201	1.43	0.0666**	0.0261	2.5500
Social network size	−0.0016***	0.0005	−2.9600	−0.0016	0.0064	−0.25	0.0147**	0.0062	2.3600
Social network centrality	−0.0058	0.0159	−0.3600	−0.0658	0.0704	−0.93	−0.1390	0.0913	−1.5200
Labour quantity	0.0061	0.0060	1.0200	0.0411	0.0318	1.29	0.0867***	0.0261	3.3200
Producer services	0.0127*	0.0067	1.9000	0.1102***	0.039	2.82	0.3202***	0.1163	2.7500
Constant	0.0084	0.0264	0.3200	−0.0327	0.1444	−0.23	−0.0521	0.2445	−0.2100

(a) Although the probabilities here are different from the group probabilities in the FMM, the farmers below the 25% quantile are the least innovative group in the sample. Thus, they are referred to as “laggards” in this study. Similarly, the farmers above the 75% quantile are the most innovative group in the sample (all belonging to the lead farmer group) and are therefore referred to as “lead farmers”

(b) ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

This result contrast highlights the unique influencing factors of lead smallholder farmers.

The impact of social network size on lead smallholder farmers is positive and significant at the 1% level, while the impact on laggards is negative and significant at the 1% level. This significant impact of social network size on the two groups confirms the importance of social networks for smallholder farmers’ technology adoption and low-carbon transition. Since smallholder farmers often lack the necessary capacity and knowledge to cope with the uncertainty brought by new technology (Banerjee et al. 2018), they need one-on-one or face-to-face communication with peers to obtain local information and to make further decisions. However, the size of social networks has opposite impacts on these two groups: larger social networks promote the low-carbon transition of lead smallholder farmers but trigger the technological lock-in of laggards. The reason for this phenomenon is that in the face of the potential uncertainty of new technology, lead farmers not only can achieve social learning and obtain mutual assistance in their social networks but also have an urgent need for heterogeneous information, such as technical training. Lead farmers can combine general knowledge acquired externally with local knowledge acquired through their social networks, thereby overcoming the over-embeddedness effect caused by homogeneous communication (Wagner et al. 2016). In contrast, laggards prefer to trust their own experience or the information conveyed by their social networks. Especially when external information is inconsistent with their knowledge, selective perception occurs, which leads to a very limited impact of external information on the technology adoption of laggards (Flor et al. 2020). The expansion of their social

networks also allows laggards to observe more cases of failure, which solidifies their resistance to new technologies and leads to technological lock-in (Bandiera and Rasul 2006; Ma et al. 2018).

Technical training promotes lead smallholder farmers’ low-carbon transition, but its effect on laggards is not significant. The different impacts of technical training confirm that lead smallholder farmers use heterogeneous information more efficiently than do laggards. Lead smallholder farmers can obtain and use more heterogeneous information through technical training to reduce technological uncertainty. Moreover, the nonsignificant impact of technical training on laggards also highlights the insufficiency of China’s current public agricultural technology extension. With the dramatic change in the agricultural technology extension system after 2000, public agricultural technology extension has been unable to meet the diversified technical needs of farmers. Hence, numerous smallholder farmers with more fragmented technology demands are marginalized (Zhou 2017; Sun 2021).

Labor quantity has a positive impact on lead smallholder farmers, indicating that farmer households with a larger labor force are more willing to take the lead in the low-carbon transition. Because the four low-carbon agricultural technologies include labor-intensive technologies, the more abundant the household labor resources are, the weaker the labor constraints that are faced, thus promoting technology adoption. However, laggards with a large labor quantity do not adopt more technologies. Although they have the ability to use low-carbon agricultural technologies, laggards usually lack the motivation to update their technology. This point is verified in the estimation results of the impact of risk attitude on laggards.

The driving effect of agricultural producer services on lead smallholder farmers and laggards is significant at the 1% and 10% levels, respectively. For smallholder farmers, compared with technical training, producer services can alleviate the constraints of household resource endowments, lower the uncertainty of technology adoption (Sun and Liu 2019), and thus help promote the low-carbon transition of all smallholder farmers.

The part-time employment level has a positive and significant impact only on laggards at the 10% level, indicating that the investment effect of nonfarm income on laggards is greater than the crowding-out effect. Since most laggards are old farmers with low household incomes, the role of agriculture in reducing the cost of living is crucial for this group (Li and Gao 2013; Zhang 2020). Therefore, farmers with high levels of part-time employment have an incentive to update their technology to achieve efficient and cost-effective farming. Although nonsignificant, educational level and land area have positive impacts, while age has a negative impact, mainly because the sampled farmers generally have the common characteristics of a small land size, old age, and a low educational level, and the differences in these traits between the sampled farmers are not significant. Social network centrality, i.e., having served as village cadres, has a negative but nonsignificant impact. Village cadres are at the central node of the social networks in a village, and this position can theoretically provide more information and resources for the transition. However, with village cadres becoming “full time”, they gradually detach from agricultural production (Yin 2017; Du 2020). Therefore, they tend not to apply the resources brought by centrality to agricultural production, leading to negative and limited effects on green technology adoption and the green transition.

The estimation result of the 50% quantile (Q50 in Table 8) verifies the robustness of the conclusions above. Compared with laggards (Q25), the effect of social network size is still negative but no longer significant; however, the coefficient of technical training becomes larger. These results indicate that the sampled smallholder farmers at the 50% quantile give more weight to heterogeneous information, thus avoiding the over-embeddedness caused by homogeneous communication to some extent. However, the nonsignificant effect of technical training indicates that these farmers are still underutilizing heterogeneous information compared to lead smallholder farmers. Regarding agricultural producer services, their effect remains significant.

Robustness tests

We first use a different model to test the robustness of the behavioral differences between laggards and lead farmers. Based on the grouping results of the FMM and the posterior probability that a farmer is classified as a lead smallholder farmer, we define farmers with a posterior probability of more than 50% as lead smallholder farmers

(receives the value of 1 and 0 otherwise). A logit model is used to analyze the behavioral influences of lead smallholder farmers. The regression results (Table 9) show that both social network size and technical training have a positive impact, although the former is nonsignificant. The previous conclusion that a higher use efficiency of heterogeneous information is the key to differentiating lead smallholder farmers from other smallholder farmers is supported.

Next, we exclude some special samples to test the robustness of the results again. We remove the following samples: first, farmers whose sales ratio is less than 50%; and, second, farmers older than 65 years old and with a land area of less than or equal to 1 mu. The main reason we drop these samples is that they pay less attention to new technologies and lack sufficient cognitive and practical abilities to adopt new technologies. Based on these criteria, 95 households were excluded. From the results of the robustness test (Table 10), there is still a difference in the utilization efficiency of heterogeneous information between the two groups of farmers: the impact of social network size on laggards (Q25) is negative, but the impact on lead farmers (Q75) is positive. The impact of technical training on laggards is nonsignificant, but its impact on leaders is significant. The former result confirms that expanding the size of social networks will promote the low-carbon transformation of lead smallholder farmers but cause the technological lock-in of laggards. The latter result verifies the importance of heterogeneous information for lead smallholder farmers.

Conclusions

In developing countries, accelerating the low-carbon transition of smallholder farmers is important and challenging. Constrained by household resource endowments and

Table 9 Robustness test by logit regression

Variables	Coefficient	St. Dev	Z value
Risk attitude	0.2830	0.1862	1.5200
Educational level	0.2033*	0.1141	1.7800
Age	−0.0073	0.0107	−0.6800
Land area	0.0104	0.0079	1.3200
Part-time employment	0.0083**	0.0036	2.2800
Technical training	0.1934**	0.0818	2.3600
Social network size	0.0348	0.0221	1.5800
Social network centrality	−0.6114*	0.3537	−1.7300
Labour quantity	0.2252**	0.0975	2.3100
Producer services	0.8281***	0.2118	3.9100
Constant	−3.1591***	0.7612	−4.1500

***, **, *Significance at the 1%, 5%, and 10% levels, respectively

Table 10 Robustness test by dropping 95 samples

Variables	Laggards (Q25)			Lead farmers (Q75)		
	Coefficient	St. Dev	<i>T</i> value	Coefficient	St. Dev	<i>T</i> value
Risk attitude	−0.0013**	0.0006	−2.0200	0.0173**	0.0072	2.4000
Educational level	−0.0223	0.0207	−1.0800	−0.1707	0.1288	−1.3300
Age	0.0018	0.0044	0.4100	0.1005*	0.0491	2.0500
Land area	−0.0002	0.0004	−0.4300	−0.0019	0.0041	−0.4600
Part-time employment	0.0071	0.0052	1.3600	0.0878***	0.0294	2.9900
Technical training	0.0002*	0.0001	1.8500	0.0019	0.0013	1.4300
Social network size	0.0005	0.0020	0.2600	0.0010	0.0016	0.6200
Social network centrality	0.0175**	0.0072	2.4200	0.1201	0.0750	1.6000
Labor quantity	0.0028	0.0027	1.0600	0.0845***	0.0237	3.5600
Producer services	0.0112	0.0073	1.5300	0.3042***	0.0773	3.9300
Constant	0.0056	0.0255	0.2200	−0.3818	0.2587	−1.4800

difficulties in accessing information and services, smallholder farmers are often in a disadvantaged position in the low-carbon transition. Therefore, it is crucial to identify lead smallholder farmers and use their information sharing, interactive learning, and mutual assistance to accelerate the transition of laggards.

Based on survey data from 643 rice farmers in Zhejiang Province, this study sets a comprehensive criterion and constructs a production function using an FMM to target lead small farmers. We also analyze the factors that influence group differentiation with a QRM to identify the driving factors of being lead smallholder farmers. The main findings are as follows.

First, the FMM results show that there is a clear differentiation in the low-carbon transition of the sampled smallholder farmers. The sampled farmers can be divided into lead smallholder farmers, survival-oriented smallholder farmers and production-oriented smallholder farmers. Lead farmers account for 38.85% of the sampled smallholder farmers. They have a higher utilization efficiency of chemical fertilizer and a higher adoption rate of four divisible low-carbon agricultural technologies. Although homogeneous in their production mode and communication channels, lead smallholder farmers are younger and more open to risk, and they also have higher educational levels and more family laborers.

Second, a higher use efficiency of heterogeneous information is the key to differentiating lead smallholder farmers from other smallholder farmers. Lead smallholder farmers can integrate general knowledge acquired externally (such as technical training) with localized knowledge acquired through social networks to achieve a higher use efficiency of heterogeneous information. In contrast, laggards rely excessively on information conveyed by their social networks. Therefore, expanding the size of social networks can promote the green technology adoption of lead farmers but can lead to technological

lock-in for laggards. This conclusion also provides a new explanation for the ambiguous relationship between social networks and technology adoption.

Third, public agricultural technology extension promotes the low-carbon transition of only lead smallholder farmers, but green producer services can effectively alleviate resource constraints and contribute to the green transition of all smallholder farmers. The heterogeneous impacts of technical training highlight the insufficiency of China's public agricultural technology extension and the necessity of social learning in low-carbon technology extension. The influence of labor quantity and agricultural producer services also proves that limited resources are the main obstacles to the low-carbon transition of smallholder farmers.

To alleviate lead smallholder farmers' resource constraints and maximize their peer effects in low-carbon agricultural technology diffusion, the government should provide more targeted support and incentives for them. First, the coverage of subsidy policies for low-carbon agricultural technology should be extended to lead smallholder farmers rather than new agricultural business entities as in the past. In addition to subsidies for low-carbon agricultural inputs, the government should add subsidies for information access, such as free broadband hardware or free mobile phone data, to meet lead smallholder farmers' needs for external information. Second, the government should provide material or moral incentives to lead smallholder farmers based on technology extension. Third, it is necessary to promote the development of low-carbon agricultural producer service organizations, for example, by increasing subsidies for green production-related equipment and green inputs. At the same time, it is also necessary to integrate the scattered demands of smallholder farmers through government purchases to truly lower the adoption thresholds of farmers and the implementation costs of low-carbon technology.

Author contribution All authors contributed to the study's conception and design. Kai Li and Qi Li were responsible for conceptualization, methodology, data collection, and formal analysis. The first draft of the manuscript was written by Kai Li, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability The datasets generated and/or analyzed during the current study are not publicly available because we collected the data through a field investigation, and they are not available from the corresponding author upon reasonable request.

Declarations

Ethical approval Not applicable.

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Consent for publication Not applicable.

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