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Technical training and rice farmers' adoption of low-carbon management practices: The case of soil testing and formulated fertilization technologies in Hubei, China

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A B S T R A C T

More than a decade ago, the Chinese government created several agricultural programs with the objective to promote food security and to foster environmental sustainability via the adoption of more eco-conscious practices in agriculture. While the overall application rate of chemical fertilizer has significantly declined, the adoption of low-carbon technologies promoted through these initiatives remains relative low—partly due to the lack of a wide-reaching systems to implement the recommended practices and farmers' lack of awareness and knowledge about the technologies. The purpose of this study is to examine the impact of technical training on low-carbon management practices, specifically on the adoption of soil testing and formulated fertilization technologies. We hypothesize that technical training and education facilitates the adoption of promoted technologies. Data for this research come from a random sample of 1115 rice farmers in Hubei, China. Using a logistic regression, we empirically examine the effect of having received formal technical training within the last 12 months on the likelihood of adopting low-carbon technologies. To account for potential heterogeneity and selection bias, we employ counterfactual framework and propensity score matching and estimate the average treatment effect for those who have received formal technical training. Our results revealed a positive and significant association between formal technical training and rice farmers' adoption of low-carbon technologies, with an average treatment effect of 0.2078. Males, younger farmers, and members of agricultural cooperatives were more likely to adopt soil testing and formulated fertilization technologies. Further, a gender analysis, conducted only with those who indicated having received technical training on low-carbon technologies, showed that trained females were more prone to adopt these technologies than trained males. Our findings provide and discuss meaningful implications for the development of future efforts to promote the adoption of low-carbon agricultural technologies in China.

1. Background

The scientific community largely agrees that the increase in concentrations of greenhouse gas emissions in the atmosphere is a driving factor of the environmental warming recorded in the last half century (Oreskes, 2004). The negative effects of greenhouse gas emissions in the atmosphere, partly produced by human activities, extend beyond the environment, posing threats to the economy and human health alike (Marino et al., 2016; Tubiello et al., 2015). In China, the largest carbon emitting country in the world, changes observed in the environmental climate have translated into economic losses in the agriculture industry. According to the National Bureau of Statistics of China (2017), agricultural losses caused by

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the impact of greenhouse gasses exceeded 503.29 billion yuan in 2016. Paradoxically, agricultural, forestry and other land use constitutes one of the largest sources of greenhouse gas emissions in the world, accounting for approximately 24% of the global carbon emission (Edenhofer et al., 2014; Robertson et al., 2000). This trend is similar for China, the largest CO_2 emitter, accounting for 30% of total global emissions (Liu, 2016; Shan et al., 2018). Thus, in light of the documented repercussion of greenhouse gas emissions, China has committed to reduce carbon emissions by 60–65% per unit of gross domestic product (GDP) by 2030, compared with 2005 levels (Cong et al., 2017).

Policymakers in China often rely on the development, implementation, and successful adoption of low-carbon practices across industries, including the agricultural sector, to accomplish the aforementioned objective by 2020 (Zhang, 2014; Liu, 2016). In agriculture, low-carbon management practices seek to mitigate carbon emissions and protect the environment without compromising farmers' financial and economic well-being (Solazzo et al., 2016; Yue et al., 2017; Zheng et al., 2017). Prior studies have described the repercussions of excessive use of fertilizers and pesticides for China's environmental, agricultural and economic systems (Pan et al., 2017; Zhao et al., 2018). The soil testing and formulated fertilization techniques are environmentally-conscious, low-carbon technologies that aim to reduce the carbon emission caused by excessive application of fertilizer, and to simultaneously improve the ecological environment (Luo et al., 2013; Chen et al., 2014). Zhen et al. (2011) documented the economic viability of these techniques—highlighting the favorable effects in terms of production cost, crop yield, fertilizer utilization rate and overall reduction of agricultural pollution.

Since 2005, the Chinese government has endorsed and encouraged the use of soil testing and formulated technologies in the agricultural sector (Zhong, 2014). Nonetheless, despite extensive efforts to promote these and other techniques, the rate of adoption of low-carbon technologies, has generally been lower than expected. The low reception of such technologies among farmers might be an artifact of lack of knowledge, perceived high risks and low cost-efficiency. Thus, the development and implementation of comprehensive and wide-reaching technical trainings—that raise awareness of low-carbon technologies and further inform farmers on the risks, production costs and spillover economic benefits of such technologies—may complement current promotion efforts of low-carbon practices in agriculture, and ultimately lead to an increased adoption rate in China.

Farm and household production models (Taylor et al., 2003; Huffman, 2011; Becker, 2013) provide guidance on the determinants that influence the decision-making process of adopting new technologies. Examples of production and farm enterprise factors include labor input, cultivated area, farm size, land transfer, and family contracted area (Taylor et al., 2003; Wei et al., 2009; Gedikoglu, 2010). In addition, research has also documented that household characteristics, such as farmers' socio-economic factors, including gender, age, and education, play an instrumental role in the decision-making process of incorporating novel technologies into agricultural practices (Defrancesco et al., 2008; Ghimire et al., 2016; Nkamleu et al., 2000; Maroušek, 2013; Suvedi et al., 2017). Within the paradigm of behavioral economics, prior research has explored the relationship between social network and farmers' adoption of novel technologies. Magnan et al. (2015) found that social network, an incubator for social learning exchanges among farmers, increased the demand for resource-conserving technology—though its diffusion was rather gradual. Similarly, Arunrat et al. (2017) found that farmer's social capital positively impacted their ability to adapt to current or forecasted events due to climate changes.

In the context of low-carbon technology adoption, recent studies indicate that the lack of awareness or sufficient knowledge is one of the major constraints in the adoption of low-carbon technologies among farmers (Huang et al., 2008; Pan et al., 2017). Technical training might then be a factor in the decision-making process for adopting low-carbon technologies (Moges et al., 2017). However, for technical training to be an effective conduit to adoption, farmers must be presented with robust, science-based evidence and relevant information of technologies, including economic viability, sustainability, risks, and other potential implications for their farm operations and budgets (Gautam et al., 2017). Pan et al. (2017) concluded that the delivery approach employed during training directly influences the adoption of low-carbon technologies, suggesting that hands-on and in-field training formats appear to be more effective approaches than one-time, lecture-based trainings.

Though the relationship between technical training and the adoption of more environmentally-conscious practices in agriculture (e.g., reduced use of pesticides and fertilizers) has been previously explored (Hu et al., 2007; Huang et al., 2008, 2012; 2015; Jia et al., 2013, 2015 Pan et al., 2017), we identify the following limitations in the extant literature. First, there is a scarcity of literature on the connection between technical training and the acceptance and adoption of soil testing and formulated fertilization technologies in China. Given that the latter are endorsed low-carbon technologies for rice production by the Central Government's Ministry of Agriculture and part of a subsidy policy (Zhong, 2014), it is crucial to determine whether technical training facilitate the actual adoption of this technology. Second, prior literature generally fails to account for potential selection bias issues and heterogeneity in their models and results. Farmers' participation and completion of technical trainings are seldom random, and this is likely to be correlated with uncontrolled and unobservable farmers' characteristics—which may also be associated with the adoption of new technologies. Disregarding self-selection when employing traditional regression methods (e.g., *logit* model or *probit* model) may result in biased inferences about the impact of technical training and the adoption of the evaluated technology (Ali et al., 2017; Guo et al., 2010; Gautam et al., 2017). In addition, heterogeneous treatment effects may also exist in farmers' likelihood to participate in technical training.

The present study aims to contribute to the literature by addressing the aforementioned limitations. The purpose of this study is to empirically examine the effects of technical training on the adoption of soil testing and formulated fertilization technologies for rice production in central China. To account for potential heterogeneity and selection bias, we employ counterfactual framework and propensity score matching when estimating the average treatment effects of receiving technical training. In addition, we discuss average treatment effects on the adoption of low-carbon agricultural practices by gender.

2. Data and econometric model

2.1. Data collection and sample

Data for this study was collected through a questionnaire administered in 2016 in the Hubei province, China. The geographical areas surveyed included 24 villages within the following 10 districts/cities: Xinzhou district in Wuhan city, Zengdu district in Suizhou City, Wuxue city, Chibi city, Zhijiang city, Zhongxiang city, Gong'an county, Zaoyang city, Macheng city, and Qianjiang city. It is important to note that there are three main paddy regions within the geographical area surveyed: single-and-double-crop rice fields in the Jianghan plain and the east region of the Hubei province, single season rice in the central region of the Hubei province, and Japonica rice in the northeast region of the Hubei province.

Multi-stage sampling was employed for the data collection. First, we randomly selected two to three towns from the list of districts/cities in the Hubei province. Then, two to three villages were randomly selected from the set of districts/cities obtained in the first step. Finally, 50 households in each village were randomly selected to answer the questionnaire. Heads of households were asked to complete the survey based on their situation in 2015. A total of 1200 farmers completed the questionnaire. After examining for inconsistencies in the data and missing values, 85 respondents were excluded from the sample. Thus, the final sample used in our research and analysis was composed of 1115 farmers.

2.2. Analytical model

2.2.1. Counterfactual framework

Unlike true experiments in the biological sciences, researchers conducting social science experiments often face difficulties in ensuring randomness in the assignment of respondents to either control or experiment groups. The resulting and potential selection bias may threaten the results of the experiment. To deal with this issue, Rubin (1974) proposed a framework— based on Neyman (1923)'s work—to analyze cause-and-effect outcomes. Using the Neyman-Rubin's counterfactual framework, we build a causal econometric model, where the control group refers to those who did not receive technical training. The econometric model can be expressed as follows:

$$Y_i = W_i Y_{1i} + (1 - W_i) Y_{0i} \tag{1}$$

(1) Farmers who receive technical training are denoted by $W_i = 1$ if farmers raised their adoption rate for low-carbon technologies and $Y_{1i} > p$; otherwise, $Y_{1i} < p$, where p is a critical value. To estimate the association between technical training with low-carbon technologies adoption, we need to investigate the farmers low-carbon behavior when $W_i = 0$. If the result is $Y_{0i} < p$, we can infer that $W_i = 1$ causes $Y_{1i} > p$.

2.2.2. Propensity score matching

In the biological sciences, randomized controlled trials are deemed as the desirable approach when aiming to estimate the effects of treatments on evaluated outcomes. In the social sciences, there is a growing interest in using nonrandomized studies to estimate the impact of treatments on outcome variables. In the context of this study, we aim to evaluate the effect of technical training on the adoption of low-carbon technologies. Propensity score, introduced by Rosenbaum and Rubin (1983) and Heckman et al. (1998), is the probability of treatment assignment, conditional on observed baseline characteristics. This method allows to design and analyze an observational study in ways that mimic some of the characteristics in a true experiment (Austin, 2011).

In our study, we divide our sample into two groups depending on whether or not a farmer had completed at least one technical training within the last twelve months of 2015. Our treatment group represents farmers who attended and received technical training on low-carbon practices in 2015, whereas the control group includes who did not engage or complete a low-carbon technology training within that period of time. We calculate the treatment effects from technical training on low-carbon technologies adoption as follows:

$$\delta_i = Y_i^t - Y_i^c \tag{2}$$

And the estimation of average treatment effects (ATE) (Rubin, 1980) is represented in equation (3):

$$\overline{\tau} = E(\delta) = E\left[Y_i^t - Y_i^c\right] = \pi E[\delta | D = t] + (1 - \pi) E[\delta | D = c] \tag{3}$$

where $D = t$ and $D = c$ correspond to treated and untreated individuals, respectively; π is the proportion of treated in our sample and $1 - \pi$ is the proportion of untreated in our sample. $E[\delta|D = t]$ represents the average treatment effect on the treated (ATT), which represents the difference in outcome of the farmers who adopted the evaluated technologies and those who did not.$E[\delta|D = c]$ is the average treatment effects on the untreated (ATU).

2.3. Variables

2.3.1. Dependent variable

Our dependent variable is defined as whether or not a farmer formally adopted formula fertilizer and soil testing technologies in rice farming. The dependent variable is coded as 1 if a farmer adopted these technologies for the first time in 2016, while 0 indicates that the farmer did not adopt the aforementioned technologies.

2.3.2. Independent variable

As described by Schultz (1964) in *Transforming Traditional Agriculture*, human capital investment plays a crucial role in transforming conventional agriculture. Technical training is one of the manifestations of human capital investment and should not be ignored in the process of promoting low-carbon technology initiatives. In the present study, receiving technical training is conceived as the main independent variable of interest. We employ a dichotomous variable, in which 1 indicates that the farmer completed at least one training related to soil testing and formulated fertilizer technologies (including lecture-based training, hands-on training and on-farm demonstrations) in 2015, and 0 denotes farmers who did not complete any training related to these technologies.

2.3.3. Covariates

Based on farm and household production models (Taylor et al., 2003; Huffman, 2011) and the basic principles of behavioral economics, we divide potential predicting factors of technology adoption into four categories[1]:

Personal characteristics. (a) *Gender*. Based on previous research (Below et al., 2012; Jin et al., 2015), we hypothesize that female farmers would prefer and use more conventional agricultural practices than males. On average, we expect a negative relationship between female famers and the likelihood of adopting the evaluated technologies. (b) *Age*. We anticipate that head of households who are older would be more likely to rely and prefer traditional agricultural practices, and thus would be less likely to adopt low-carbon management practices. (c) *Health*. We anticipate that farmers who indicate they have bad health would be more likely to pay more attention to the environment and may be more likely to adopt soil testing and formulated fertilizer (Rahman, 2003; Oluwole et al., 2009; Salemdeeb et al., 2017). (d) *Education*. A positive relationship between farmers' level of education and the likelihood of accepting new technologies (Burton, 2014) is expected.

Family characteristics. (a) *Quantity of labor inputs in agriculture*. Labor force is an essential input for agricultural production.

[1] We also consider the basic rule of propensity score matching, which indicates that the covariates should affect farmers' adoption of soil testing and formulated fertilizer technologies and technical training, but cannot be affected by technical training.

Table 1
Descriptive statistics of variables.

Variables		Variable description	Mean	Standard deviation
Dependent variable	*act*	Whether farmers adopted soil testing and formulated fertilizer technology, binary variable, 0 = no, 1 = yes	0.1767	0.3816
Independent variable	*train*	Whether farmers participate in any technical training, binary variable, 0 = no, 1 = yes	0.2323	0.4225
Personal features	*gender*	The gender of household head, binary variable, 0 = female, 1 = male	0.7013	0.4579
	age	The age of household head, continuous variable (year)	55.5776	9.1285
	health	The health condition of household head, binary variable, 0 = unhealthy, 1 = healthy	0.6457	0.4785
	education	Education of household head, continuous variable (year)	7.1991	3.3473
Family characteristics	*labor*	The quantity of labor force in agricultural, continuous variable (person)	1.9731	0.7346
	job	Whether the household head have off-farm-work, binary variable, 0 = no, 1 = yes	0.2942	0.4559
Production and management	*area*	Family contracted land area, continuous variable (Mu)	19.0725	36.8935
	transfer	Land transfer, binary variable, 0 = no, 1 = yes.	0.2861	0.4521
	fertility	Whether the land is fertile or not, binary variable, 0 = no, 1 = yes	0.3363	0.4727
	plots	Number of rice planting plots, continuous variable	6.6224	9.4055
Social networks	*cooperative*	whether to join a cooperative, binary variable, 0 = no, 1 = yes	0.0592	0.2361
	exchange	Whether to exchange rice planting experience with other farmers, binary variable,0 = no,1 = yes	0.6018	0.4897

Considering that soil testing and formulated fertilizer technologies requires adequate labor investment, we anticipate that the more labor inputs a household has, the more likely they are to adopt soil testing and formulated fertilizer technologies. (b) *Whether the head of household has off-farm-work*. A household head having off-farm-work would reduce farming time and increase the probability of excessive use of fertilizer. Consequently, we hypothesize that farmers' off-farm-work has a negative influence on soil testing and formulated fertilizer technology adoption.

Production and management in agriculture. (a) *Family contracted land area* is continuously measured in Mu (=0.0667 ha). Based on the scale effect principle, the larger the contracted land area, the more likely farmers are to adopt soil testing and formulated fertilizer technology. (b) *Land transfer.* Higher frequency of land transfers would most likely result in an instability of land management. Therefore, we expect that farmers whose enterprises have transacted more land transfers would be less willing to adopt soil testing and formulated fertilizer. (c) *Soil fertility*. Soil fertility may affect farmers' decisions in terms of fertilizer adoption, including soil testing and formulated fertilizer technologies. For example, a decrease in soil fertility may create an incentive to adopt new technologies to counteract potential negative effects (Ajayi et al., 2007). However, other studies show that farmers who perceive that their land require minimal fertility inputs—in other words, more fertile responsive soils—are more likely to adopt technologies with the expectation that the use of an extra technology may increase returns (Vanlauwe et al., 2010; Mponela et al., 2016). In this study, we measure this variable via farmers' perceptions about the fertility of their land. (d) *Number of rice planting plots*. The number of rice planting plots would increase the difficulty in applying the formula fertilizer by soil testing technology. Thus, we expect to observe a negative relationship between the number of rice planting plots and low-carbon technologies adoption.

Social network. We choose two variables to measure social network. First, we measure if the farmer is affiliated to a cooperative. In general, cooperatives aim to provide and inform farmers of new technologies available along with their respective costs, benefits, and risks for agricultural practices. Cooperatives may be an additional source of information and promotion of new technologies. Secondly, we assess the level of knowledge exchange in terms of rice farming among farmers. We suggest that mutual exchange of farmers is conducive to the diffusion of information of new technologies, and thus hypothesize a positive and significant association with the likelihood of adopting formulated fertilizer by soil testing.

Table 2
The mean comparison of variable *act* for trained and untrained farmers.

Variable	Trained (n = 259)	Untrained (n = 856)	T test
act	0.3745(0.0301)	0.1168(0.0110)	−9.9317***

Note: ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% levels, respectively, the numbers in brackets denote standard error.

Table 1 presents the descriptive statistics for the variables employed in this study. As shown, 17.67% of the farmers in this study adopted formulated fertilizer and soil testing technologies for the first time in 2016. In addition, 23.23% of our sample of rice farmers indicated having completed at least one technical training in 2015.

As a preceding step to the evaluation of the proposed econometric model, we performed a *t*-test analysis to test for differences in the adoption of low-carbon technology between farmers who received training, and those who did not. The results for the bivariate analysis are shown in Table 2. Our results indicate that trained farmers are more likely to apply low-carbon technologies in comparison to their counterparts.

3. Results

To examine the association between farmers' adoption of formulated fertilizer by soil testing technologies and technological training, we estimate a *logit* model. We account for potential selection bias and heterogeneity using propensity score matching. The following section presents the results of the estimations of the *logit* and propensity score matching models.

3.1. Logit model

We built a *logit* model to illustrate the correlation between farmers' adoption of formulated fertilizer by soil testing technologies.[2] Table 3 shows the results of a logistic regression. Our results show that technical training is significantly and positively related to the use of formulated fertilizer by soil testing technology. In addition, male individuals, younger farmers and farmers' social networks (i.e., being a member of a cooperative and exchanging rice farming knowledge and experiences with other growers) are

[2] To test for potential multicollinearity in our model, we estimated the Variable Inflation Factor (VIF) values. For all variables, the VIF values were less than 10, which lead us to conclude that multicollinearity was not a concern in our model.

Table 3
Results of logistic regression model.

Variable		Coefficient	Marginal effects
	training	1.1333***(0.1840)	0.1421
	gender	0.8418***(0.2302)	0.1056
Personal characteristics	*age*	−0.0301***(0.0098)	−0.0046
	health	−0.0369(0.1880)	−0.0079
	education	−0.0207 (0.0244)	−0.0026
Family characteristics	*labor*	−0.0334(0.1228)	−0.0042
	job	−0.0846(0.1910)	−0.0106
Production and management	*area*	0.0006(0.0018)	0.0001
	transfer	−0.2257(0.1959)	−0.0283
	fertility	−0.0864(0.1875)	−0.0108
	plots	0.0087(0.0103)	0.0011
Social networks	*cooperative*	1.0513***(0.2884)	0.1318
	exchange	0.4952**(0.1864)	0.0621
	constant	−0.6418 (0.6780)	–
Log pseudo likelihood		−452.07	
Wald chi2		125.60	
Pseudo R^2		0.1306	

Note: ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% levels, the numbers in brackets denote robust standard error.

significant predictors of farmers' adoption of the aforementioned low-carbon practices in rice production. We calculated the marginal effects for each variable in the logit model and the results are presented in Table 3. The marginal effect of technical training on the adoption of formulated fertilized by soil technology was 14.21%. Though there was a positive and significant correlation between these variables, we are limited in terms of inferring about causality—that is due to potential self-selection and heterogeneity in the model. Thus, the propensity score matching method is used to adjust for any selection bias in the model.

3.2. Propensity score matching model

We use the logistic regression model in Table 3 to estimate the propensity score. We use the nearest-neighbor matching to illustrate the matching effect. As Fig. 1 shows, the density of propensity score in "treatment" and "control" are different before matching, which may be indicative that an unsuitable comparison of sample characteristics exists in the "control" group. After performing propensity score matching, we find that the density of propensity score between the two groups is similar. Hence, we determine that the sample characteristics in the "treatment" and "control" group are reasonably comparable given the analogous results in radius matching and kernel matching.

3.2.1. Analysis of average treatment effect

(1) *Average treatment effect of technical training on soil testing and formulated fertilizer adoption*

We combine three matching methods including nearest-neighbor matching, radius matching, and kernel matching to estimate the average treatment effect, and use a bootstrap with 500 repetitions to calculate standard errors. The results of nearest-neighbor matching are provided in Table 4.

From Table 4, we note that the average treatment effect for the treatment group is significant, which provides evidence for the hypothesis that technical training does have a substantial effect on the adoption of formulated fertilizer by soil testing technology. We

Table 4
The average treatment effect of training on soil testing and fertilizer recommendation.

	Coefficient	Standard error
ATT	0.2078***	0.0533
ATU	0.1404**	0.0479
ATE	0.1563***	0.0414

Note: ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% levels, and standard error are calculated using bootstrap with 500 repetitions.

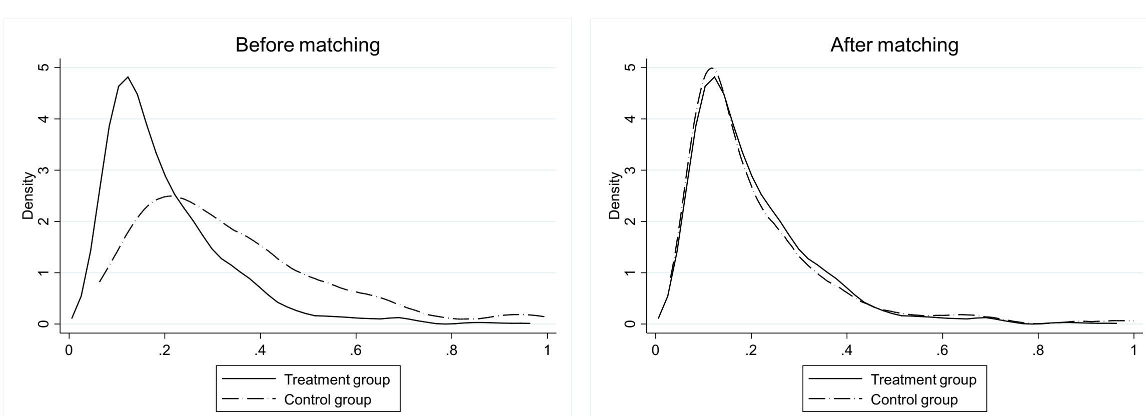

Fig. 1. The density of propensity score before and after nearest-neighbor matching in "treatment "and "control" group.

also find that the average treatment effect for the untreated (ATU) and the average treatment effect (ATE) are 0.1404 and 0.1563, respectively.

(2) Average treatment effect by gender

Further, we divided our sample into male and female groups and estimated the average treatment effect by gender. As seen in Table 5, the average treatment effects (ATT) for both males and females in our sample are positive and significant. Our results revealed that overall trained female farmers are more likely to adopt soil testing and formulated fertilizer recommendations than trained males.

3.3. Balance test and robust test

3.3.1. Balance test

We employed a balance test to evaluate the matching effect in our propensity score matching model (that is the balance between treatment and control group). The results for the balance test are provided in Table 6. As shown, the matching bias dropped below 10% after matching the variable *age*. Additionally, most variables are significant (the *t*-value of variable of *fertility* and *health* are also reduced) before matching. However, after the matching is performed, all variables are no longer significant. This is indicative of a well-matched and corrected selection bias for our model.

3.3.2. Robustness test

We use radius matching and kernel matching to verify the robustness and convergence of our results. Table 7 shows the influence of different matching methods to the average treatment effects for the treatment group in our experiment. The consistency and convergence in results for either of these methods provides evidence of robustness for the results presented in this study.

4. Discussion

In this study, we empirically examine the association between technical training and rice farmers' adoption of a low-carbon technology (i.e., formulated fertilizer and soil testing techniques) in the Hubei Province, China. We hypothesize that technical training facilitates the decision-making process of adopting low-carbon technologies in China. Further, based on prior research and behavioral-economic models (Taylor et al., 2003; Huffman, 2011), we proposed that the adoption of low-carbon technologies is also influenced by the following factors: a) farmers' personal characteristics (i.e., gender, age, health status, and level of education); b) household characteristics (i.e., agricultural labor input contributed by the household, and head of household's non-agricultural labor), c) farm production management attributes (i.e., contracted land area, land transfer, soil fertility, and number of planting plots), and d) farmers' social network.

Our results provided evidence to support the hypothesis that formal technical training is positively and significantly associated with farmers' adoption of low-carbon technologies. These results suggest that behavioral change, such as adoption of new technologies, require comprehensive, deliberate and targeted interventions that inform and guide farmers on the risks, productions costs, and economic decision-making processes of adopting low-carbon technologies. This is consistent with behavioral change theories that assert that knowledge alone is seldom sufficient to lead to a change in intention or behavior (Fishbein and Ajzen, 1975; Ajzen and Fishbein, 1980; Prochaska and Velicer, 1997). Moreover, consistent with previous research, farmers' characteristics (i.e., age and gender, social network) were significant predictors of farmers' adoption of soil testing and formulated fertilization technologies (Magnan et al., 2015; Arunrat et al., 2017; Defrancesco et al., 2008; Ghimire et al., 2016; Nkamleu et al., 2000; Maroušek, 2013; Suvedi et al., 2017). In particular, males, younger farmers, and members of agricultural cooperatives were more prone to adopt these technologies. As proposed by Magnan et al. (2015), farmers' social network including agricultural cooperatives and organizations are facilitating venues for social learning and knowledge exchange. In addition, younger farmers might be more receptive to try, test and adopt new technologies, as they might be less dogmatic in terms of their belief systems of agricultural practices (Pan et al., 2017). Finally, the gender analysis reveals that among those who indicated receiving formal training within the last 12 months, trained females were more likely to adopt low-carbon measures than their male counterparts. These results have important ramifications for future policies on low-carbon technology adoption as feminization of agricultural labor in China continues to increase (Song and Vernooy, 2010).

Table 5
Average treatment effect by farmers' gender.

Gender	Treatment/Control	ATT	Standard error	Z-value
male	212/570	0.1827***	0.0575	3.18
female	47/286	0.2432*	0.1043	2.33

Note: ***, ** and * indicate statistical significance at the 0.1%, 1% and 5% levels, and standard error are calculated using bootstrap with 500 repetitions.

5. Conclusions

More than a decade ago, the government of China launched a series of policies and initiatives with the objective of ensuring food security while simultaneously fostering agricultural sustainability. From 2005 to 2010, the Chinese Ministry of Agriculture sponsored a national "*soil testing and fertilizer recommendation*" program to encourage the adoption of low-carbon management practices for the major cereal crops in the country, including rice (Zhang, 2014). After the enactment of this program, the overall application rate of chemical fertilizer declined (Qi, 2013). However, the adoption rates of low-carbon technologies promoted through the program were lower than expected—partly due to the lack of a wide-reaching system to implement the recommended practices, and the lack of awareness or sufficient knowledge about the technology and its implications for farmers (Li et al., 2013).

Our study underscores the importance of technical training in the effort to increase the adoption of low-carbon technologies among rice farmers in China. Based on our findings, we draw the following conclusions: (1) technical training increases the likelihood of farmers' adoption of formulated fertilizer by soil testing technologies; (2) gender, and its interaction with technical training, plays a substantial role in the decision-making process of adoption a low-carbon technology. Particularly, trained female farmers are more likely to adopt the formulated fertilizer and soil testing technology than trained male growers; (3) age and farmers' social network are associated with farmers' adoption of the evaluated low-carbon technologies. Overall, our study provides evidence of the facilitating role of technical training in the adoption of more environmentally-friendly practices in agriculture.

5.1. Policy implications

These conclusions have important implications for low-carbon management initiatives in rice production—a staple crop that feeds more than half of the global population (Wang et al., 2005). For China, the largest producer and consumer of rice worldwide,

Table 6
The results of balance test between treatment and control group.

Variable	Unmatched / Matched	Mean Treatment	Mean Control	T-test	Bias (%)	reduce |bias| (%)
gender	U	0.8185	0.6659	4.75***	35.4	
	M	0.8196	0.8392	−0.59	−4.5	87.2
age	U	52.907	56.386	−5.44***	−38.6	
	M	52.914	51.992	1.15	10.2	73.5
health	U	0.6950	0.6308	1.89	13.6	
	M	0.6941	0.7490	−1.38	−11.6	14.4
education	U	7.0772	7.2360	−0.67	−4.8	
	M	7.0353	6.9922	0.15	1.3	72.8
labor	U	2.0772	1.9416	2.61**	18.5	
	M	2.0667	2.0745	−0.11	−1.1	94.2
job	U	0.3784	0.2687	3.41***	23.6	
	M	0.3804	0.3608	0.46	4.2	82.1
area	U	32.977	14.866	7.07***	37.3	
	M	27.490	22.874	1.36	9.5	74.5
transfer	U	0.3938	0.2535	4.41***	30.3	
	M	0.3843	0.3804	0.09	0.8	97.2
fertility	U	0.3668	0.3271	1.18	8.3	
	M	0.3647	0.3255	0.93	8.2	1.2
plots	U	10.170	5.5491	7.08***	39.4	
	M	8.7804	8.0941	0.80	5.9	85.1
cooperation	U	0.1506	0.0315	7.27***	42.2	
	M	0.1412	0.1373	0.13	1.4	96.7
exchange	U	0.7375	0.5608	5.15***	37.6	
	M	0.7333	0.7608	−0.71	−5.8	84.5

***, ** and * indicate statistical significance at the 0.1%, 1% and 5% levels.

Table 7
The influence of different matching methods to ATT.

	Nearest-neighbor matching	Radius matching	Kernel matching
ATT	0.2078***(0.0533)	0.1885***(0.0425)	0.1954***(0.0390)

***, ** and * indicate statistical significance at the 0.1%, 1% and 5% levels, and standard error are calculated using bootstrap with 500 repetitions.

these findings provide further guidance for the formulation and implementation of future policies, especially as China aims to fulfill the Paris agreement[3] pledge while meeting the national and international growing food demand (NRDC, 2017). First, to enable a greater adoption of low-carbon management practices, such as formulated fertilizer and soil testing technology, policymakers should consider the positive effects of including technical training in the delivery of their programs. Timely and wide-reaching technical training allows farmers to increase familiarity with recommended technologies, as well as inform them of the risks and uncertainties, economic viability (e.g., economic cost and economic benefits), and environmental and sustainability (e.g., hazards of using high-chemical fertilizers for the environment and soil quality) implications of adopting a low-carbon technology. Second, when developing and promoting new low-carbon management programs, policymakers can maximize the effects of technical training by considering the effects of gender role, age and farmers' social network on the adoption of low-carbon technologies. Traditionally in China, rural farming households have been patriarchal. However, due to current migration patterns in rural china (i.e., more men out-migrate for work to urban areas), women staying in rural areas are substantially spending more time on agricultural production (Mu et al., 2011; Wu et al., 2016). Hence, the implementation of prospective low-carbon programs should account for these migration trends and gender-based intra-household time allocation—which might result in a greater adoption rate for assessed technologies as trained female growers are more prone to accept novel technologies. Moreover, didactics employed in trainings should provide spaces for farmers to learn from each other's experiences, and to interact with farmers who have successfully adopted the technology in question. Similarly, promotion efforts should target farmers' social network, such as farming associations and groups.

5.2. Limitations

Though this study significantly contributes to the literature about the impact of technical training on the adoption of low-carbon management practices among rice farmers, it nevertheless has a set of limitations. First, the random sample used in this research comes from the Hubei province, the fifth largest producer of rice in China. Thus, the generalizability of our result is restricted to only this province. Future research should consider including samples from the other largest rice producing provinces (i.e., Hunan, Heilongjiang, Jiangxi, and Jiangsu province). Second, the analysis in this study is performed with non-experimental, cross-sectional data. Though the results from the robustness tests are consistent with the results obtained in the propensity score matching analysis, we are cautious in claiming any causal effect between technical training and adoption. Further research should be conducted with longitudinal data in which participants are randomly assign to groups. Third, the characteristics of training programs are relevant to the likability and even the level of adoption of new technologies. In this study, we discuss training from a generic perspective. Nonetheless, future research should compare the effectiveness of training programs with different characteristics (e.g., online training versus in-person training, hand-on/on-farm demonstration training versus lecture-based training, one-time session training versus multiple-session training, etc.). Finally, we account for potential self-selection bias, a major problem in social science research, using propensity score matching analysis.

[3] China—the largest carbon emission country around the world—has pledged to lower carbon emissions per unit of gross domestic product by 60–65 percent (from the 2005 level) in year 2030 (NRDC, 2017).

However, prospective research might benefit from controlling farmers' attitudinal and psychological variables, such as self-efficacy, consciousness, motivation and attitude towards adaption, and prior technical training experience.

Declaration of conflicting interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and publication of this article.

Compliance with Ethnical standards

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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