Evaluation on impacts of agricultural extension program for reducing agricultural NPS pollution by propensity score matching

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Abstract

Purpose – The goal of this paper is to measure average change in fertilizer use of farmers that was brought about by their participation in the agricultural extension program.

Design/methodology/approach – In this paper, we use the propensity score matching method to evaluate effects of agricultural extension programs for reducing farmers' fertilizer input. The approach involves two main steps. First we estimate the probability of farmers' participation behavior in agricultural extension program. Second, using propensity score kernel matching, we estimate the result of average treatment affect for the treated (ATT) farmers.

Findings – To some extent, we find that the China-UK program achieves beneficial effects on farmers' fertilizer use. We also are able to evaluate to a limited extent the impact of individual elements of the program. We find that demonstration zones may have had a counterproductive effect while the posters may be the most effective program element.

Research limitations/implications – a significant limitation of our paper is the small size of the participated observations. This is no doubt contributed to the problem of statistically insignificant ATT estimates for most of our treatments. Since it appears that the effects of extension programs such as the China-UK program are slight, future research should strive to have much larger sample of farmers.

Originality/value – This paper provides a valuable contribution to our understanding of the effects of agricultural extension programs in China. The methodological and empirical aspects of this paper will help improve the design and evaluation of future such programs.

Keywords Fertilizer use, Agricultural non-point source pollution, Agricultural extension program, Participation, Propensity score matching, ATT

JEL codes: Q24; Q28

1. Introduction

Overuse of fertilizer leads to agricultural non-point source (NPS) pollution. Nitrogen and phosphorus that cannot be absorbed by crops leaves the farm and affects underground water, lakes and rivers. This can result in significant environmental and human health impacts (Brett, et al. 2011). As shown in the First Report of National Pollution Investigation by Ministry of Environmental Protection, National Bureau of Statistics, and Ministry of Agriculture of the People's Republic of China in 2010, agriculture contributes 2.7 million tons of Nitrogen, which accounts for 57.2% of the annual total N emission to China's waters. Since 1999, various national laws and rules have been promulgated with the goal of reducing agricultural NPS pollution. However, it is difficult to control agricultural NPS pollution just through laws. One important reason is that Chinese farmers have limited knowledge of methods of "rational fertilization," which refers to the situation in which means yield gains can be achieved at lower levels of fertilizer use (Rao, 2011).

A change in farmers' fertilizer decisions is essential to achieving a reduction in agricultural

NPS pollution in China. After pursuing alternative policies, a growing number of researchers have expressed interest in using agricultural extension programs to affect farmers' decisions (Brent, et al. 2002). Researchers have found that Chinese farmers are more likely to use environmentally friendly methods if they have received training or guidance of agricultural technologies and practices (He, et al. 2006; Gong, et al. 2008). A numbers of training classes and educational programs that aim to reduce farmers' fertilizer input have been implemented to date. The effectiveness of the educational and extension program depends on whether the information from educational and extension program induce a positive change in farmers behavior of applying fertilizer. In this paper, we use propensity score matching (PSM) methods to estimate the effects of one such program.

In 1983, Rosenbaum and Rubin published a seminal paper on propensity score analysis. They illustrated both theory and application principles for a variety of propensity score models and proposed propensity score matching as a method to reduce the bias in the estimation of treatment effects with observational data sets. Since this work, the propensity score method has grown at a rapid pace and wildly used to estimate average treatment effects. Godtland et al. (2004) used propensity score matching methods to examine the impact of a pilot FFS program on farmers' knowledge with the data set from a survey of potato farmers in Cajamarca, Peru. They suggested that FFS had the potential to raise productivity substantially, by about 32% of the average value in a normal year. Pufahl and Weiss (2009) evaluated the effects of agri-environment (AE) programmes and found a positive and significant treatment effect of AE programmes on the area under cultivation, in particular grassland, resulting in a decrease of cattle livestock densities. Mezzatesta et al. (2012) used propensity score matching to estimate how much additional conservation is achieved by federal cost-share programs in the U.S. Looking at six types of conservation practices, they found that cost-share programs achieve statistically significant levels of additionality for each practice, but that there was significant variation in the levels of additionality across the different practices.

To the best of our knowledge, Chinese researchers have not used the propensity score matching to evaluate the effects of agricultural extension program on farmers' fertilizer behavior. However, several studies have used these methods to measure treatment effects in other contexts. Chen et al. (2010) evaluated the effects of improved upland rice technology on rice farmers' income in southwestern Yunnan province by using the non-parametric propensity score matching method and found that the improved upland rice technology had positive and robust effects on upland rice farmers' income. Wang et al. (2009) estimated the treatment effects of vocational training in rural Guangdong province and found that the treatment effect for the treated was lower than the average treatment effect and the latter is lower than the treatment effect for untreated. Zhang and Wang (2010) estimated the effects of job training by using propensity score matching method and found that both pre-job training and the job training can increase rural labors' earnings while the effects of the pre-job training is more obviously.

In this paper, we use the propensity score matching method to evaluate effects of agricultural extension programs with a goal of reducing farmers' fertilizer inputs. Our paper analyzes farmers' participation decision using data from a farmer survey in Shaanxi province in China. Our goal is to measure average change in fertilizer use of farmers that was brought about by their participation in the program. This is done by, controlling for variables that affect a farmer's participation decision, comparing the fertilizer use of the participating farmers with those who did not participate. The approach involves two main steps. First we estimate the probability of farmers' participation in the programs. This bivariate model has four categories of variables: demographic variables, planting variables, awareness variables, and policy variables. We find that famers' participation behavior was significantly affected by whether they use machine, farm income rate, village had program, access to training classes. The second step uses propensity score kernel matching to estimate the result of average treatment affect for the treated (ATT) farmers. In our estimates of ATT for different treatments we find some evidence that that, after controlling for endogenous selection, the China-UK program did affect farmers' fertilizer use in a favorable way.

This paper is organized as follows. After this introduction, we will provide some background of agricultural extension programs and present the statistics of the China-UK program that provides the motivation for this paper. We then summarize the survey data used in this paper, which was conducted in 2011 in China. After that, we report our methodology and variables description. Next, we provide the estimation results for the liner regression of expected fertilizer use, the probability of farmers' participation decision, the balance test, and the ATT. Finally, we discuss our econometric results and policy implications.

2. Agricultural extension programs

In this paper, we include two agricultural extension programs. The first one is the soil testing and formulated fertilization program, a national program that implemented all over the country since 1990s. In this program, a soil test is conducted and then a recommendation of the appropriate fertilizer amount is provided to farmers. The second program, our primary focus, is a local program and only implemented in Shaanxi Province.

This program is called "Improving Livelihoods on Farms by reducing non-point N Pollution through Improved Nutrient Management," which was funded by the UK's Foreign and Commonwealth Office and by China's Ministry of Agriculture from January 2007 to December 2009. Hereafter we will refer this as the China-UK program. This program was led by Dr. Tong Yanan from Northwest A&F University in China Shaanxi Province and Dr. David Powlson from Rothamsted Research in the UK, also included other participating units such as local extension workers, Farmers Association and farmers. The overall objective of the project was to provide access for poor farmers to information that will enable them to use N fertilizer in a rational way, reducing application rates while increasing crop yields and economic returns. The project's goals, therefore, were to reduce both environmental pollution and the wasting of valuable resources.

The China-UK project consisted of the following parts: 1) An assessment of farmer and community perceptions to understand reasons for current N overuse; 2) Collection and analysis of relevant technical data on rates and timing of N fertilizer relevant to the environment (climate, soils, cropping systems) of Shaanxi Province; 3) Farm based experiments using the results from step 2 to measure how fertilizer changes can affect farm productivity and profitability; 4) Using results from points 2 and 3 above, develop information delivery programs that inform farmers of the benefits of rationalized N use; 5) Analysis of information delivery programs will be tested in collaboration with farmers. In our paper, participation means that farmer voluntary participate in the fourth elements and receive information from the program.

The China-UK project is quite different from previous programs in China. First, farmers are involved in and are the main subjects of this program. Second, the China-UK program did the experiments with farmers and showed the results to the farmers. Finally, this program was trying to spread the information to farmers not to the government only. This paper will evaluate the extent to which the information delivery system (step 4) was successful in reducing fertilizer application rates. In the next section, we will present the statistics about the program which provide the motivation of this paper.

We summarize the evidence gathered by the China-UK project in the experimental analysis of the effect on nitrogen application and crop yields (step 3 above) in Table 1. The China-UK program conducted farm-based experiments for winter wheat and summer maize in three villages. The content of the experiments was as follows. Selected farmers changed their fertilizer input rates according to the project recommendation, while holding other farming practices unchanged. It should be emphasized, that these farmers' changes were not voluntary, and they received subsidies for the action of changing fertilizer input and compensation if they have loss of yield from the program.

Table 1: Changes of the farm based experiment for winter wheat and summer maize in 2010

	Village	**Fertilizer changes**	**Yield Changes**	**Input cost changes**	**Yield profit change**	**Total profit changes**
Unit		**Kg/ha**	**Kg/ha**	**Yuan/ha**	**Yuan/ha**	**Yuan/ha**
wheat	Village 1	-70	+185	-306	+332	+639
	Village 2	-18	+117	-79	+221	+290
	Village 3	-22	-39	-96	-70	+26
	Average	-37	+88	-160	161	+318
maize	Village 1	-167	+208	-728	+312	+1040
	Village 2	-155	+298	-674	+447	+1121
	Village 3	-160	+261	-694	+392	+1086
	Average	-161	256	-699	384	+1082

Source: Zhang Shulan, Report in 2010 conference of China-UK project.

As seen in the above table, the average fertilizer input for both wheat and maize decreased in all three villages. Despite the N reduction, except for wheat in Village 3, yields increased for both crops. Notably, the reduction of fertilizer application for maize is about 72% of past application rates. On the other hand, we can easily see that the fertilizer input decreased and profits increased in all three villages for both wheat and maize. Even in village three, famers' savings from reduced fertilizer input for wheat more than made up for the loss in yield. Finally, the average increase of profits in three villages is 318 Yuan/ha for wheat and 1082 Yuan/ha for maize.

The experimental results from these three villages indicate that there is a great potential to reduce farmers' fertilizer use, thus reducing agricultural NPS pollution, without economic losses. However, the goals of the program will be achieved only if farmers participate in the agricultural extension program, i.e. receive the program's information, and then change their behavior as a result.

3. Estimation methods

Before we use propensity score matching to estimate the ATT of the programs, we use liner regression to predict one of outcomes, the expected fertilizer use. Next we use a probit model to estimate the probability of farmers' participation in the programs. We mainly present the estimation methodology for ATT in this section.

In our survey, farmers can be divided into two groups, group I and group J. Farmers who received a treatment are in group I, and those who did not are in group J. Define an indicator variable, D, which equals one if a farmer received a treatment; and zero if a farmer did not receive. Further, define the outcome variables Y for each farmer as their fertilizer input. We will sometimes write $Y^i\left(D=1\right)$ to emphasize that the i^{th} farmer is defined as a farmer who has received a treatment.

There are two outcomes of fertilizer use for each farmer. The fertilizer input is Y_1 if a farmer received a treatment, and is Y_0 if a farmer did not receive a treatment. We can only observe one of these two outcomes of fertilizer use for any given farmer in our survey, i.e. for treated farmer i, we only can observer Y_1^i. What we want to estimate is the treatment effect of the agricultural extension program, i.e. the difference between the fertilizer use by treated farmers, Y_1^i less than what they would have used without participating, Y_0^i. The average treatment effect on the treated group of farmers:

$$ATT = E[Y_1^i - Y_0^i] = E[Y_1^i - Y_0 \mid D=1] = E[Y_1^i \mid D=1] - E[Y_0^i \mid D=1] \qquad (1)$$

We can observe $E[Y_1^i \mid D=1]$, but cannot observe $E[Y_o^i \mid D=1]$. Matching estimators can be used to estimate this unobserved counterfactual outcome, i.e. the fertilizer use of farmer from group I if he or she had not received a treatment, $\hat{Y}_0^i = E[Y_0^i \mid D=1]$. The basic idea in matching is to use the non-treated farmers to estimate what the treated farmers would have done without the program. To correct for bias that would be introduced by simply comparing the means of the two groups, a set of covariates, *X*, is used so that similar farmers are compared.

Two assumptions are made when we apply the matching estimate to estimate the ATT. The first condition, which was proposed by Heckman et al. (1997) states that the outcome Y must be independent of treatment conditional on the set of observable covariates, i.e., $Y \perp D \mid X$. The covariates X should affect both the farmer decision on participation of the agricultural extension program and the outcomes. If the first condition, also called unconfoundedness assumption is satisfied, then the outcome Y is also independent of participation of the program on the propensity score, i.e., $P = P(D=1 \mid X)$. The propensity score is defined as the probability of farmers' participation in the China-UK program conditional on *X* and is estimated by a binary choice model, a probit model in our paper.

The second assumption is the overlap assumption which states that the probability for both treated and control farmers is positive for the vector of covariates X, i.e., $0 < P(D=1 \mid X) < 1$. This assumption implies that the probability for each treated farmer to match the group of non-treated farmers with a similar set of covariates *X* is positive. As we will see below, the overlap condition is imposed by dropping those observations for which it is not satisfied, i.e., it is not possible to estimate the ATT for those observations for which there are no suitable matches.

The matching estimators for $E[Y_1^i \mid D=1]$ and $E[Y_o^i \mid D=1]$ in equation (1) are:

$$E[Y_1^i \mid D=1] = \frac{1}{I}\sum_i (Y_1^i) \qquad (2)$$

$$E[Y_0^i \mid D=1] = \frac{1}{I}\sum_i (Y_0^i) = \frac{1}{I}\sum_i \sum_j W(i,j)(Y_0^j) \qquad (3)$$

Where Y_0^j is the observed outcome for the farmers who did not receive any treatment, W(i, j) is the weights given to the jth non-treated farmer used for estimating the ith farmer's fertilizer use if he or she had not treated. There are a variety of matching algorithrms that can be used to calculate W(i,j).

Therefore, the matching estimator for the ATT in equation (1) is

$$\hat{ATT} = E[Y_1^i \mid D=1] - E[Y_0^i \mid D=1] = \frac{1}{I}\sum_i \{(Y_1^i) - \sum_j W(i,j)(Y_0^j\} \qquad (4)$$

4. Data and Variables

4.1 Data Description

In this paper, we use the data from 626 face-to-face surveys that were carried from May to October, 2011 in nine villages located in Yangling District, Wugong County, and Jinyang County of Shaanxi Province. Farmers were randomly selected to interview for our survey in these villages and two of the villages were sites of the China-UK program. Information of the program was spread to other villages by broadcast or communication between farmers in different villages. The surveys were implemented by 20 graduate students majoring in agricultural economics and management in Northwest A&F University.

In the survey area, winter wheat and summer maize are the main crops while some farmers plant kiwis, tomatoes and other vegetables. The average number of family members and members participating in farm are 5.3 and 2.54 respectively. Farmers are mostly middle age (average age is 52) and only 18% farmers' education level is above high school, which means relatively low in this area. As with much of China's farming operations, the area of farms in the surveyed group is small, averaging only 0.3 ha. There is some substantial diversity in farms with annual net profit ranging from 1,000 Yuan and over 50,000 Yuan (157.4 and 7870 dollar at the 2012 exchange rate). The average N fertilizer input for the whole year 2010 from our survey data is 151.7 kg/ha.

4.2 Outcome and Independent variables

The outcome variables of interest in our analysis are 1) farmer's fertilizer input (kg/ha), which is obtained from our survey, and 2) the difference between expected fertilizer use, which is estimated by a linear regression model, and actual fertilizer use. The treatment variable is farmers' participation in the China-UK and soil testing and formulated fertilization program. There are five ways for farmer to participate in China-UK program: farmer field school, demonstration zone, farmer meeting, farmer to farmer training, and poster for reducing fertilizer use. The farmer field school delivers information on rational fertilization and teaches the planting technology to farmers in the field. Demonstration zones show the experimental results and details of fertilizer input in the demonstration area to farmers. Farmer meetings gather farmers together to deliver information about fertilizer applications. Farmer to farmer training is a kind of smaller farmer meeting at which the speaker is also a farmer. Finally, posters are pasted on walls beside the street and freely provided to the farmers.

The treatment group consisted of farmers who reported receiving treatment from the program while the control group is made up of farmers who did not. Table 2 reports farmers' participation in soil testing and formulated fertilization program and different components of China-UK program. Thirty-five farmers reported participating in the soil testing and formulated fertilization program. The participation rate for each treatment is relatively low and only 10% percent of the survey respondents reported receiving one or more of the program's components. Demonstration zone and farmer to farmer training are the most popular ways for farmers to participate in the China-UK program. There are 24 farmers and 30 farmers participated in these two components respectively.

Table 2: Participation in different components of China-UK program

program	participation	
	number	%of sample
soil testing and formulated fertilization program	35	5.6%
Components of China-UK program		
Farmer Field School	20	3.2%
Demonstration zone & Farmers Viewing	24	3.8%
Farmer Meeting	21	3.3%
Farmer to Farmer training	30	4.8%
poster, leaflet for reducing fertilizer use	19	3.0%
Participation one or more components	67	10.7%
Participation two or more components	31	4.9%
Participation three or more components	8	1.3%

4.3 Covariate description

The descriptive statistics for the other variables used in our paper are presented in Table 3. The statistics are broken for two groups, those who participated in one or more components of the China-UK program and those who did not. These variables are used in the propensity score equation (probit) in which treatment is the dependent variable.

The demographic information includes gender, age, education, and years of farming experience. There are intuitively plausible reasons to expect these demographic variables to affect the propensity to participate in the program. Generally older farmers tend to refuse receiving new farming methods because they are risk averse and do not want to change their planting habits dramatically (Adesina and Zinnah, 1993; Mauceri et al., 2005; Ge, 2010). Thus, we expect that age will be negative to farmers' participation. We also expect that well educated farmers will be better in dealing with the information from the program, making them more likely to participate in the program.

Eight variables capture characteristics of the farmers' operations. The farming income ratio is calculated by dividing the family's income from farming by their total income. The labor ratio is the numbers of family members involved in farming divide total number of family members. Land area represents the farmer's total arable land in hectares. An important distinguishing feature for farmers is whether they make use of any machinary for farming, typically small machines for tilling the soil; this is captured using a dummy variable that equals one if farmer uses any machinery. Finally, crop types are also affect both the farmers' participation in the program and effects of extension program. A higher ratio of farming income or bigger land area means that a farmer's life depends more heavily on agricultural production. Since the China-UK program and soil testing and formulated fertilization program seek to control agricultural NPS pollution by reducing farmers' fertilizer input, we expect that farmers who depend more heavily on agricultural production are more likely to participate in the program to minimize the cost of production. Similarly, we expect that the labor ratio and machine variables will be positively correlated with participation in the program.

Awareness of agricultural NPS pollution, environmental polies and sustainable agriculture policies are captured in three dummy variables based on yes-no response to questions about these issues. The coefficients on these dummy variables will capture whether knowledge of these issues is translated into action through participation in the program. Our expectation is that farmers are aware of agricultural NPS pollution will pay more attention to environmental protection, which will lead farmers' attention to sustainable agriculture. In this paper, all these three variables are expected to positively influence farmers' participation in the program.

The final set of variables presented in Table 3, captures attitudes toward the various policies. Data were collected on whether the respondents lived in a village where the program was implemented, their access to and experience with training classes (other than the China-UK and soil testing and formulated fertilization program), whether they get fertilizer information from friends or relatives, their support of laws to restrict fertilizer use, their support of taxes on agricultural NPS pollution, and the farmer's expectation of subsidies for reducing fertilizer use. These variables are likely to affect whether a farmer participates in the program. With one exception (expectation of subsidy), the set of treatment variables are dummy variables based on responses to yes-non responses to questions. Furthermore, this set of variables is expected to result in a higher probability of farmers' participation.

A critical step in the matching procedure is to ensure that the matching creates a balanced sample, i.e. one that is consistent with the unconfoundedness condition: $Y \perp D \mid X$. There are seven models in our paper, so we will not present the balance test of every model. In table we take the results of participation in China-UK program as an example because that China-UK program is the main extension program we considered in this paper. We provide the summary statistics and Balance test of the covariates in table 3.

Table 3 Summary Statistic and balance test for covariates

variables	Unmatched			Matched		
	Treated mean N=38	Control mean N=356	Diff in means	Treated mean N=33	Control mean N=356	Diff in means

Personal Characteristics						
Gender	0.53	0.52	0.01	0.52	0.58	-0.06
Age	52.37	51.58	0.79	51.58	50.94	0.64
Education	0.21	0.15	0.06	0.15	0.21	-0.06
Years for farming	28.4	29.18	-0.78	29.18	30.52	-1.34
Farm Characteristics						
Using machine	0.89	0.88	0.01***	0.88	0.88	0.00
Land area	5.03	5.28	-0.25	5.28	6.75	-1.47
Labor ratio	0.50	0.50	0.00	0.50	0.54	-0.04
Farming income ratio	0.72	0.71	0.01***	0.71	0.76	-0.05
Planting others crops	0.13	0.09	0.04	0.09	0.15	-0.06
Planting kiwi	0.05	0.06	-0.01***	0.06	0.03	0.03
Planting corn	0.84	0.91	-0.07	0.91	0.94	-0.03
Planting wheat	0.87	0.91	-0.04	0.91	0.91	0.00
Awareness						
of agricultural NPS	0.34	0.33	0.01	0.33	0.24	0.09
of environmental protection policies	0.39	0.39	0.00	0.39	0.3	0.09
of eco-agriculture policies	0.55	0.48	0.07**	0.48	0.58	-0.10
Policies						
Village has program	0.47	0.45	0.02**	0.45	0.39	0.06
Communication with friends	0.26	0.24	0.02**	0.24	0.18	0.06
Accessible training class	0.29	0.24	0.05***	0.24	0.18	0.06
Experience of training classes	0.24	0.18	0.06***	0.18	0.12	0.06
Expectation of subsidy amount	3.74	3.79	-0.05	3.79	3.85	-0.06
Support laws to limit fertilizer use	0.89	0.88	0.01***	0.88	0.88	0.00
Support tax on pollution	0.61	0.64	-0.03	0.64	0.61	0.03

As we can see from the table above, before matching the average values of nine variables are different between treated and control group at at least 5% significant level. After matching, however, there are no significant differences between the treated and control groups, suggesting that a valid counterfactual has been created. This balancing is achieved in part because five of the treated observations are dropped because they were no on the support, i.e. there are no untreated observations with roughly the same propensity scores. Similar balancing tests were carried out for every model. With one exception, the results of the balancing test are similar to those presented in table 6. The exception is when the treatment is participation in both the China-UK program and soil testing and formulated fertilization program (model 1). In this case, the variable training class access is still significantly biased after matching. This could be explained that we have the question “Is there any training class other than China-UK program in your village or town?” in our questionnaire, so the training class access is independent of China-UK program not soil testing and formulated fertilization program.

5. Estimation results

5.1 Linear Regression

We use a liner regression model to estimate the expected fertilizer use so that we can compare the difference of a farmer's actual fertilizer use with the expected fertilizer use for a farm with such characteristics. The dependent variables is the total fertilizer input, the explanatory variables are age, gender, education, years for farming, if farmer using machine for farming, labor ratio, farming income ratio, and land area for wheat, corn, kiwi, other crops.

Table 4: results of regression model for predicting expectation fertilizer use

Variables	Coefficient.	Std. Err.	P>t
Gender	0.55	0.80	0.49
Age	1.56	13.52	0.91
Education	-11.73	18.71	0.53
Years for farming	-0.35	0.75	0.64
Using machine	-12.98	14.63	0.38
Labor ratio	37.45	27.79	0.18
Farming income ratio	63.20**	29.35	0.03
Plant area for wheat	10.31	8.17	0.21
Plant area for corn	17.81**	8.13	0.03
Plant area for kiwi	10.19*	5.56	0.07
Plant area for other crops	67.06***	7.96	0.00
constant	-36.09	38.92	0.35
R-squared	0.38		
Numbers of observations	450		

***, **, *, represent 1%, 5%, 10% significant level respectively

According to this result, the variable farming income ratio, planting area for corn, kiwi and other crops affect total fertilizer input. The R-squared of this model is only 0.38, which is not surprising – an individual farm's actual fertilizer use is likely to vary for many reasons not included in this linear model. Since there is concern of farmers' overuse of fertilizer in China, we would expect to find differences between farmers' actual fertilizer use and the average level that is captured by the liner regression model. This difference, therefore, is and indicator of over- or under-use of fertilizer and is one the outcomes that we will attempt to evaluate using propensity score matching.

5.2 Propensity score

Before we obtain the ATT estimator, we must first estimate the propensity score using a probit model, where the dependent variable is the treatment decision. We have seven different treatment specifications. In model 1, we estimate the probability that farmer participated in both China-UK program and soil testing and formulated fertilization program. The dependent variable in model 2 is that farmer participated in any of the information delivery components of China-UK program. The next five models (3-7) are the same as model 2 except we drop one element of the program. for example, a farmer is considered to the treated in model 3 if he or she participated in any element of the China-UK program except farm field school. For the specific elements dropped in each model, refer to table 7. The estimated results of the probit model are presented in Table 5, where the explanatory variables used in the estimation are those in Table 3.

Table 5 estimated results of the probit model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Personal Characteristics							
Gender	-0.151	-0.253	-0.308	-0.213	-0.202	-0.162	-0.175

Age	0.003	0.013	0.015	0.010	0.009	0.006	0.010
Education	-0.024	0.106	0.154	-0.178	-0.675*	0.224	0.304
Years for farming	0.008	-0.000	-0.002	0.001	-0.012	0.007	0.007
Planting Characteristics							
Using machine	1.44***	1.291***	1.233***	1.319***	1.341***	1.282***	1.333***
Land area	-0.003	0.005	0.008	0.006	-0.007	-0.001	0.023
Labor ratio	-0.784	-0.887	-0.842	-0.456	-1.152*	-1.051	-1.157*
Farming income ratio	1.454***	1.632***	1.633***	1.670***	1.832***	1.740***	1.700***
Planting others crops	0.583	0.488	0.58	0.037	0.584	0.092	0.651
Planting kiwi	-2.157***	-1.548**	-1.521**	-1.324*	-0.874	-1.608**	-1.661**
Planting corn	-0.967*	-0.711	-0.718	-0.584	-0.399	-0.573	-0.843
Planting wheat	-0.601	-0.226	-0.218	-0.206	0.0126	-0.668	-0.191
Awareness							
of agricultural NPS	-0.274	-0.235	-0.132	-0.490	-0.027	-0.064	-0.601*
of environmental protection policies	0.170	0.256	0.245	0.314	0.318	0.290	0.288
of eco-agriculture policies	0.172	0.127	0.120	-0.037	0.360	-0.026	0.034
Policies							
Village has program	0.752***	0.745***	0.851***	0.628**	0.588*	0.772***	0.835***
Communication with friends	-0.498***	-0.557**	-0.481*	-0.575	-0.570*	-0.815***	-0.447
Accessible training class	1.139***	1.177***	1.220***	1.197***	1.147***	0.929**	1.440***
Experience of training classes	0.388	0.370	0.384	0.39	0.630	0.020	0.293
Expectation of subsidy amount	0.183	0.200	0.166	0.257	0.167	0.248	0.144
Support laws to limit fertilizer use	0.603*	0.783**	0.945**	0.346	0.861**	0.962***	0.699*
Support tax on pollution	-0.242	-0.218	-0.289	0.235	-0.545**	-0.247	-0.119
constant	-3.126**	-4.200***	-4.366***	-4.533***	-4.237***	-4.011***	-4.129***

***, **, *, represent 1%, 5%, 10% significant level respectively

In this paper our principal interest in the probit results is to calculate the propensity score to carry out the matching estimation of the ATT. Nonetheless, there are some results in these models that are worth highlighting. Four variables are positive and significant in all seven models: Using machine, Village has program, Accessible training class, Farming income ratio. Clearly these variables, consistent with our expectations, are positively correlated with participation in the China-UK program. Three other variables are significant and negative in five or more of models: Planting kiwi, Communication with friends, and Support laws to limit fertilizer use. This is somewhat less intuitive, but does suggest that there is selection bias in the program. For example, kiwi farmers are less likely to enroll, as people who mostly get fertilizer information from friends or relatives.

5.3 Treatment effects(ATT)

In this section, we provide the estimation results on ATTs for different treatments. The ATT is estimated based on the equation 4 by using propensity score kernel matching. We have two outcomes variables of interest. First we look at the effect of treatment on the total actual fertilizer input per hectare per year from our survey. Second, we use the difference between total actual fertilizer input and the level of fertilizer input estimated by a liner regression model. This second outcome variable should be an indicator of the extent to which the farmer is overusing or underusing fertilizer compared to the mean level given the farming practices being employed (the result in Table 4).

As indicated above, we estimate the ATT for seven treatments and table 7 below shows all the ATTs estimates. A positive ATT value for outcome 1, total fertilizer input, suggests that the average farmer who received that treatment applied more fertilizer (in kilograms per ha) than they would have without treatment. A positive ATT value for outcome 2, indicates that, on average, treatment led farmers to increase their fertilizer use (in kilograms per ha) as measured relative to the best linear expectation for the fertilizer use given the farms characteristics. For both outcome 1 and 2, the hope of the extension programs is that the ATT will be negative, indicating that participation in the program led to a reduction in fertilizer use.

Table 6: ATT for different treatment

	Treatment	Outcome 1: Total fertilizer use			Outcome 2: Residual of actual fertilizer use and estimated fertilizer use		
		ATT	Stand. Er	t-stat	ATT	Stand. Er	t-stat
1.	China-UK and soil test	8.70	27.75	0.31	-18.17	25.46	-0.71
2.	Full China-UK program	-112.19	86.86	-1.29*	-89.01	83.43	-1.07*
3.	drop farm field school	-31.10	37.67	-0.83	-25.79	30.84	-0.84
4.	drop demonstration zone	-92.73	65.50	-1.42*	-116.54	45.69	-2.55*
5.	drop FTFT	-103.98	51.30	-2.03*	-48.77	32.30	-1.51*
6.	drop farmer meeting	-4.75	40.30	-0.12	-13.10	32.59	-0.40
7.	drop poster	26.35	33.29	0.79	19.70	25.49	0.77

***, **, *, represent 1%, 5%, 10% significant level respectively

When the treatment is participation in both China-UK and soil testing and formulated fertilization program (treatment 1), the ATT estimate indicates a negative but statistically insignificant impact on farmers' fertilizer use, and a positive causal impact on fertilizer overuse in statistically insignificant level. Our estimate is that participation in both programs induce farmers to apply 9.2 kg/ha more fertilizer than they would have had they not participated and, relative to the expected level a 22.6 kg/ha reduction. At least in part because of the small number of treated farmers and the great variation in fertilizer use observed, neither of the ATT estimates are statistically significant. The lack of statistical significance means that we cannot with any reasonable level of confidence state that Treatment 1 had any impact on fertilizer use, either positive or negative.

Similarly, we see that when the China-UK program is evaluated alone (treatment 2) there is no statistically significant effect. In this case, we find a favorable impact on both total fertilizer use and fertilizer overuse. We estimate that participating farmers applied 56.2 kg/ha less fertilizer than they would have applied had they not participated, and 37.4 kg/ha below when measured relative to the estimated fertilizer use.

To some extent, we find that the China-UK program contributes more to reducing farmers' fertilizer along than the soil testing and formulated fertilization program, though the differences are not statistically significant. This might be explained by the scale and regional characteristics of two programs. The soil testing and formulated fertilization program, as a national program, had implemented in all over the country. China-UK program, as a local program, had implemented only in Shaanxi Province that obtained more concentration and frequent communication between farmers and the experts in the program.

Ideally it would be interesting to evaluate each element of the program. However, we do not have enough observations for each element to carry out such analysis. Instead, we drop one components of the China-UK program at a time to obtain an indication of which elements of the program had the greatest impact on fertilizer use. Consider first treatment 3, in which we drop farmer to farmer training. When this is done, the ATT for outcome 1 changes from -56.2 to -65.7 and becomes significant at the 10% level. We find, therefore, that in terms of total fertilizer use, the program would be slightly more effective at reducing nitrogen use if the program had not included the farmer to farmer training. At the other extreme, when poster is dropped from the treatment (treatment 7), the effect on both outcomes becomes positive, though not statistically significant. This suggests that the poster element of the program was particularly important to achieving any favorable outcome from the program; when only the poster element is excluded, we estimate that the program would have been counterproductive. Similarly, when farmer meeting is dropped (treatment 6) the effectiveness of the program falls very close to zero.

Table 7 indicates that the China-UK program without demonstration zone component significantly leads to a reduction in farmers' fertilizer use. In other words, it appears that the demonstration zone component actually leads more fertilizer input. This might be caused if the farmers ignored the details about rational fertilizer use, only paying attention to the results of the experiments in the program by viewing the demonstration zone. Perhaps farmers want to keep the same productivity as the demonstration area and then applied more fertilizer in their own land area to achieve those results. At the other extreme, if the poster component is excluded from the treatment, we find the program leads participating farmers to increase their fertilizer use and overuse. This suggests, somewhat surprisingly, that the posters may have been the most effective component of the China-UK program.

6. Robust checks

In this section, we check the robustness of our empirical results.

First, we use a variety of matching estimators that differ in the model specifications on the weights: two matching methods (kernel and nearest neighbor), two kernel functions (Gaussian and Epanechnikov), and four bandwidths (bandwidths = 0.02, 0.06, 0.1, and 0.15)

The results are almost the same.

Secondly, we performed bootstrapped simulations to test whether the estimation results

Outcome 1: Total fertilizer use

		ATT	Stand. Er	CI	
1	China-UK and soil test	1.86	50.19	−107.73	87.51
2	Full China-UK program	−0.12	51.55	−106.17	96.95

3	drop farm field school	−1.24	58.00	−120.17	108.86
4	drop demonstration zone	−18.54	65.49	−167.37	87.79
5	drop FTFT	−3.37	55.91	−120.04	94.83
6	drop farmer meeting	−3.92	77.04	−161.63	123.82
7	drop poster	11.87	61.18	−123.80	121.05
Outcome 2: Residual of actual fertilizer use and estimated fertilizer use					
		ATT	Stand. Er	CI	
1	China-UK and soil test	−6.55	40.62	−91.85	68.03
2	Full China-UK program	−10.98	42.51	−101.31	60.03
3	drop farm field school	−13.63	48.99	−129.98	67.70
4	drop demonstration zone	−36.54	52.28	−158.34	52.52
5	drop FTFT	−11.72	43.17	−98.30	60.76
6	drop farmer meeting	−15.66	64.08	−149.02	92.34
7	drop poster	−6.34	49.72	−106.05	79.19

It should be acknowledged that estimation of the ATT using propensity score matching is based on the unconfoundedness assumption. If there exist unobserved covariates that influence both enrollment and outcome variables, then the estimated ATT may be biased. For example, unobserved characteristics may explain why some farmers choose to voluntarily adopt conservation practice even when funding is available. Although the unconfoundedness assumption cannot be verified in practice, Rosenbaum (2002) developed a method to test the extent to which a matching estimator is sensitive to hidden bias. Specifically, Rosenbaum's approach assumes that the propensity score, $P(D=1|X)$, is influenced not only by observed covariates X, but also by an unobserved covariate. As a result of this unobserved covariate, farmers that are matched based on similar propensity score values, may actually differ in their odds of enrolling by a factor of Γ, where $\Gamma=1$ represents the baseline case of no hidden bias. The higher the level of Γ to which the ATT remains statistically different from zero, the more robust are the estimation results to the potential influence of hidden bias.

We conduct a Rosenbaum bounds sensitivity analysis to estimate the extent to which selection on unobservables may bias the estimates of the ATT (Rosenbaum 2002; DiPrete and Gangl 2004).

7. Conclusion

In order to reduce agricultural NPS pollution, Chinese agricultural extension programs are increasingly trying to educate farmers and reduce fertilizer use through voluntary measures. The evaluation of the effects of such programs is crucial because it will determine whether the programs contribute to the reduction of agricultural NPS pollutions and are worth continuing. In this paper, we carry out one such analysis, using propensity score matching to estimate the impacts of the China-UK program on farmers' fertilizer use. Propensity score matching has the ability to reduce the bias that would result if one simply compared the treated and control groups.

We do not find any statistically strong support for a positive effect of the programs. In part this is due to the small number of farmers who actually participated in the programs; the vast majority of the farmers in the programs did not report participating in any of the program's multifaceted element. Looking at those farmers who did participate, to some extent, we find that the China-UK program achieves beneficial effects on farmers' fertilizer use.

The results of model 2 suggest that there may be a favorable impact on both total fertilizer use and fertilizer overuse; participating farmers applied 56.2 kg/ha less fertilizer they would have applied if they not participated, and our estimate of their overuse finds a reduction of 37.4 kg/ha. We also are able to evaluate to a limited extent the impact of individual elements of the program. We find that demonstration zones may have had a counterproductive effect while the posters may be the most effective program element. Again, the statistical significance of our results is quite slight.

A significant limitation of our paper is the small size of the participated observations. This no doubt contributed to the problem of statistically insignificant ATT estimates for most of our treatments. Since it appears that the effects of extension programs such as the China-UK program are slight, future research should strive to have much larger sample of farmers.

Despite of the limitations, we consider the propensity score matching to be a useful method for evaluation of agricultural extension programs that seek to achieve environmentally beneficial outcomes. This paper can provide a valuable contribution to our understanding of the effects of agricultural extension programs in China and improve the design of future such programs.

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