Sustainability **2014**, *6*, 6644-6665; doi:10.3390/su6106644

OPEN ACCESS

sustainability

ISSN 2071-1050

www.mdpi.com/journal/sustainability

Article

The Impact of Agricultural Extension on Farmer Nutrient Management Behavior in Chinese Rice Production: A Household-Level Analysis

Dan Pan

Institute of Poyang Lake Eco-economics, Jiangxi University of Finance and Economics, Nanchang 330013, China; E-Mail: pandan@jxufe.edu.cn; Tel.: +86-791-8381-0553; Fax: +86-791-8381-0892

External Editor: Marc A. Rosen

Received: 13 August 2014; in revised form: 16 September 2014 / Accepted: 18 September 2014 / Published: 29 September 2014

Abstract: Agricultural nutrients play a critical role in food production and human nutrition in China. Against this backdrop, agricultural extension services are essential for providing farmers with knowledge and information about nutrient management. By using a propensity score-matching (PSM) approach, this study examines the impact of agricultural extension on farmer nutrient management behavior. Survey data about rice farmers in seven provinces of rural China are used. The empirical results indicate that participation in agricultural extension has a positive impact on rationalizing farmer nutrient management behavior. However, this impact is trivial. Compared with non-participating farmers, the reduced ratio of total fertilizer use and total inorganic fertilizer use by participating farmers is only 1.7% to 3.7%, and the improved ratio of the total organic fertilizer use and the level of soil-testing-based fertilizer use by participating farmers is only 1.008% to 1.173%. Additionally, the causal impacts of agricultural extension participation on nutrient management behavior tend to be higher for more educated, risk-loving and larger-scale farmers. This study reveals that China faces great challenges in implementing improved nutrient management practices for hundreds of millions of farmers through extension services. The findings also have important implications for China's extension system to meet the objectives of improving nutrient management.

Keywords: agricultural extension; nutrient management; propensity score matching; China; rice production

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1. Introduction

Nutrients, such as nitrogen (N), phosphorus (P), potassium (K), micronutrients, and others, are essential for plant growth, food production and, ultimately, for adequate human nutrition [1]. It has been estimated that the survival of nearly half of the world's population depends on the use of agricultural nutrient inputs [2], whereas lack of access to nutrients in most African countries is a primary cause of low crop yields and food shortages [3]. Over the past 50 years, China has successfully achieved food self-sufficiency for its rapidly growing population. China is now feeding approximately 22% of the global population with only 7% of the global arable land area. This accomplishment was achieved primarily by increasing the use of chemical fertilizer nutrients, especially N and P. China is now the world's largest producer, consumer and importer of chemical fertilizers, consuming over 1/3 of the world's chemical fertilizers and accounting for approximately 90% of the increase in global fertilizer consumption since 1981 [4]. However, Chinese agriculture uses far more chemical fertilizers per unit of crop production than comparable systems in Europe or North America [3]. In 2010, Chinese agriculture consumed 28.1 Tg N as synthetic fertilizer, exceeding consumption in North America (11.1 Tg N) and the European Union (10.9 Tg N) combined [5]. Numerous agronomic and economic studies under both experimental conditions and on farm fields provide conclusive proof that the overuse of chemical fertilizers has become widespread across China. For example, the average amount of N fertilizer used in the major rice producing regions of China is 195 kg ha^{-1}, which is 47% higher than the recommended rate [6]. The oversupply of nutrients or an imbalance between nutrients reduces the efficiency of nutrient use. As a consequence, the mean N-use efficiency in crop production in China has decreased drastically from 32% in 1980 to 26% in 2005 and is much lower than the efficiency achieved in many developed countries [7].

Nutrient losses from agriculture have resulted in serious environmental stress by increasing greenhouse gas (GHG) emissions and by polluting ground and surface water through N leaching [8]. According to the official report from the Ministry of Environmental Protection of China in 2010, the annual loadings of N and P from the agricultural sector into the nation's water bodies reached 2.7 and 0.3 Tg, which contributed to approximately 60% of the total N and P loads. The high rate of N fertilizer use has led to large N losses in the form of ammonia (NH_3) volatilization and N leaching into groundwater and lakes [9]. Furthermore, the manufacture and use of N fertilizers are estimated to have contributed to approximately 30% of agricultural GHG emissions and more than 5% of China's total GHG emission in 2007 [10]. To address the country's widespread water quality and other nutrient-related environmental issues (e.g., soil acidification, N deposition, and climate change), drastic improvements in nutrient management that will allow the Chinese food production industry to simultaneously feed the growing human population and decrease the environmental impacts of food production are one of the great challenges China faces in the 21st century.

In an effort to address these food security and environmental challenges related to agricultural nutrient use, China has implemented wide-ranging nutrient management practices to increase the efficiency of N and P use [11]. However, most of these nutrient management technologies, programs, and recommendations have not been adopted by farmers. The primary reason for this problem is rooted in the lack of knowledge and information by end users, because the majority of the hundreds of millions of farmers have received limited education about the value and efficient use of plant nutrients [12].

Hu *et al.* [13] found that, with appropriate N fertilizer application technology, N fertilizer use could be reduced by more than 30% without lowering (and potentially even increasing) rice yields. Cui *et al.* [14] found that using improved nutrient management technologies could reduce N fertilizer use by 40% without lowering maize yields, compared with current farming practices. Therefore, the timely delivery of science-based fertilizer recommendations through education, training and extension services is essential for improving nutrient use efficiency and for reducing the over-application of nutrients [15].

However, given the importance of agricultural extension services for proper nutrient management, little empirical work has been conducted to examine this area of farm management in China. To the best of our knowledge, the only two exceptions can be found in [10,16]. Using data collected on the North China Plain, Huang *et al.* [10] showed that through training and scientist-guided on-farm pilot experiments, N-fertilizer use could be reduced by 22% in maize production without compromising yields. Using data from 813 maize farms, Jia *et al.* [16] found that improved N management training could significantly reduce farmer N fertilizer application by 20%.

A major drawback of the above studies is that they do not properly control for potential differences between participants and farmers in the comparison group (non-participants), making it difficult to draw definitive conclusions. To identify the impacts of agricultural extension participation, an evaluation must construct a credible counterfactual outcome; that is, a study must estimate the nutrient management behavior of participants if they had not participated in the agricultural extension programs. Failure to do this will bias the corresponding impact estimates. To fill this gap, we employ a propensity score matching (PSM) method to overcome this unobserved counterfactual problem. We use the PSM model because it can create experimental conditions in which participants and non-participants are randomly assigned, providing an unbiased estimation of the treatment effects, and it can be used to identify a causal link between agricultural extension participation and farmer nutrient management behavior. To the best of our knowledge, this is the first study to use the PSM method to evaluate the impact of agricultural extension participation on farmer nutrient management behavior.

Rice production is selected for this study for two reasons. First, rice is the number one crop in terms of the unit per area yield in China, reaching 6.777 t ha^{-1} in 2012, which is 1.359 and 1.155 times greater than the unit per area yield for wheat and maize. Second, as discussed above, there is suspected overuse of agricultural nutrients in rice production.

The rest of the paper is organized as follows. The next section presents an analytical framework and methodology, followed by a presentation of the data and descriptive statistics in Section 3. The empirical results and findings are discussed in Section 4. The last section concludes with key findings and policy implications.

2. Analytical Framework and Methodology

2.1. Decision to Participate in Agricultural Extension

Following [17,18], the economic rationale that drives the analytical framework underlying farmer participation in agricultural extension is the maximization of perceived utility. The decision about whether to participate in an agricultural extension program depends on the utility the farmer expects to derive from participation. Farmer participation only occurs when the expected utility of participation

(U_P) is greater than the utility without participation (U_N), *i.e.*, $U_P - U_N > 0$. The difference between the utility with and without participation may be denoted as a latent variable D_i^*, such that $D_i^* > 0$ indicates that the utility with participation exceeds the utility without participation. Therefore, the D_i^* is not observable, but can be expressed as a function of the observed characteristics and attributes denoted as Z_i in a latent variable model as follows:

$$D_i^* = \beta Z_i + \varepsilon_i \tag{1}$$

and

$$D_i = \begin{cases} 1, \, if \; D_i^* > 0 \\ 0, \, otherwise \end{cases} \tag{2}$$

where D_i is a binary indicator variable that equals 1 if a farmer participates in an agricultural extension program and is otherwise zero; β is a vector of the parameters to be estimated; Z_i is a vector of explanatory variables, including the household and farm-level characteristics; and ε_i is the error term, which is assumed to be normally distributed.

The probability of participation in an agricultural extension program by a farmer based on observable characteristics can then be estimated using either a binary probit or a logit model:

$$\Pr(D_i = 1) = \Pr(D_i^* > 0) = \Pr(\varepsilon_i > -\beta Z_i) = 1 - F(-\beta Z_i) \tag{3}$$

where F is the cumulative distribution function for ε_i, which is commonly assumed normally distributed in the probit model or extreme value distributed in the logit model. The extreme value distributed error gives the function its logistic distribution.

In can be noted that the decision by a farmer to participate or not in an agricultural extension program is dependent on the farm, as well as farmer characteristics; therefore, it relies on each farmer's self-selection rather than on random assignment.

2.2. Impact of Agricultural Extension Participation on Farmer Nutrient Management Behavior

A commonly used approach to evaluate the impact of participation in an agricultural extension program on the outcome of farmer nutrient management behavior is to include a dummy variable equal to the one in the outcome equation indicating whether the farmer participated in an agricultural extension program, but otherwise equaling zero, and then applying an ordinary least squares (OLS) regression. This may be expressed as follows:

$$Behavior_i = \alpha X_i + \gamma D_i + u_i \tag{4}$$

where $Behavior_i$ represents the nutrient management behavior of farmer i, X_i is a vector of farm-level and household-level characteristics, such as the age and education of the farmer, the farm size, the farmer risk attitude, and soil quality variables; D_i is a dummy variable, $D_i = 1$ for participation in an agricultural extension program and $D_i = 0$ otherwise. The coefficient γ in the specification captures the impact of agricultural extension participation on farmer nutrient management behavior. This approach, however, is likely to generate biased estimates because it assumes that participation in an agricultural extension program is exogenously determined; however, it is potentially endogenous. Participation in agricultural extension programs is not random and is strongly correlated with unobservable household and farm characteristics (e.g., managerial skill, motivation, and so on) that may be correlated to nutrient management behavior. This may arise from farmer self-selection for participation in an agricultural extension program or from strategic program placement. The issue of selection bias occurs if unobservable factors influence both the error term of the participation equation ε_i in Equation (1) and the error term of the nutrient management behavior u_i in Equation (4), resulting in correlation between the two error terms. Therefore, estimating Equation (4) with ordinary least squares will lead to biased estimates.

Researchers have proposed various methods to avoid selection bias [19]: (1) an experimental study in which participants can be randomly assigned to either control or treatment groups, but this is not possible for *ex post* studies; (2) the instrumental variables (IV) approach, in which a major limitation is that it normally requires a valid instrument that determines the treatment status but not the outcome variable, which is an arduous task in empirical studies [20]. Moreover, the IV procedure assumes that the treatment variable only induces a parallel shift (intercept effect) on the outcome variable, implying that the interactions between extension participation and other covariates does not exist; (3) Heckman's two-step method; however, this two-step procedure depends on the restrictive assumption that the unobserved variables are normally distributed [21]; (4) a difference-in-differences estimation, which examines the effect before and after a treatment and between treated and untreated groups; therefore, this method is limited to studies with longitudinal data; and (5) a propensity score-matching method, which, unlike the methods mentioned above, requires no assumption about the functional form specifying the relationship between outcomes and outcome predictors. Therefore, the difficulty of finding valid instrumental variables can be avoided, and cross-sectional data collected at one point in time can be used [22,23].

Based on these attributes and the data availability, we chose the PSM method to control for selection bias in our analysis.

2.3. The Propensity Score-Matching (PSM) Method

2.3.1. Average Treatment Effect (ATE)

The objective of this study is to estimate the average treatment effect (ATE) of agricultural extension participation on farmer nutrient management behavior. An ideal situation to estimate the ATE is to simply compare two outcomes for the same unit: when the unit is assigned to the treatment and when it is not [24]. In the context of this study, for example, the ATE could be estimated by comparing nutrient management behavior when the farmer is enrolled in an agricultural extension program and when not enrolled. In the absence of experimental data, the biggest challenge to estimating an ATE is that we do not know what the nutrient management behavior would have been if the farmer had not participated in the agricultural extension program. Therefore, construction of an unobserved counterfactual remains the basic problem of the evaluation of ATEs [25]. Rosenbaum and Rubin [26] developed the PSM approach, which is most commonly used in non-experimental settings to overcome the unobserved counterfactual PSM constructs of a statistical comparison group by matching every individual observation of participants with an observation having similar characteristics to the group of non-participants. In essence, the PSM model creates the conditions of an experiment in which participants and non-participants are randomly assigned, providing an unbiased estimate of treatment effects, and it can be used to identify a causal link between agricultural extension participation and farmer nutrient management behavior.

According to [26], the ATE (Δ_i) in a counterfactual framework can be defined as follows:

$$\Delta_i = Y_i^1 - Y_i^0 \tag{5}$$

where Y_i^1 and Y_i^0 denote the nutrient management behavior of farmer i who participates in the agricultural extension program and farmer i who does not participate in the agricultural extension program, respectively. Estimating the impact of agricultural extension participation on the ith farmer from Equation (5) would be misleading due to the problem of missing data. Normally, we can only observe either outcome Y_i^1 or Y_i^0 for one farmer at a time, not both. The normally observed outcome can be expressed as follows:

$$Y_i = D_i Y_i^1 + (1 - D_i) Y_i^0 \tag{6}$$

where D is a dummy variable that indicates agricultural extension participation. The average effect of the treatment on the treated (ATT) is defined as the difference between the expected value of the outcome by participants while participating in the agricultural extension program and the expected value of outcome they would have received if they had not participated in the program. Following Smith and Todd [23], the ATT, which is the parameter of interest in this empirical research, can be defined as follows:

$$ATT = E(Y_i^1 \mid D_i = 1) - E(Y_i^0 \mid D_i = 1) = E(Y_i^1 - Y_i^0 \mid D_i = 1) \tag{7}$$

Data on $E(Y_i^1 \mid D_i = 1)$ are available from the program participants, but data on $E(Y_i^0 \mid D_i = 1)$, which is the counterfactual outcome, are not observable for a given farmer. Therefore, what we can usually observe is the ATE, which can be expressed as follows:

$$\begin{aligned} ATE &= E(Y_i^1 \mid D_i = 1) - E(Y_i^0 \mid D_i = 0) \\ ATE &= [E(Y_i^1 \mid D_i = 1) - E(Y_i^0 \mid D_i = 1)] + [E(Y_i^0 \mid D_i = 1) - E(Y_i^0 \mid D_i = 0)] \\ ATE &= ATT + E(Y_i^0 \mid D_i = 1) - E(Y_i^0 \mid D_i = 0) \end{aligned} \tag{8}$$

If participation in agricultural extension is randomly assigned, the participation dummy variable D is statistically independent of the outcome (Y_i^1, Y_i^0), and the mean outcome of untreated individuals $E(Y_i^0 \mid D_i = 0)$ can be used as a proxy for $E(Y_i^0 \mid D_i = 1)$. However, in non-experimental surveys, the treated and untreated groups may not be the same before receiving treatment. Therefore, $E(Y_i^0 \mid D_i = 0)$ cannot be used as a proxy for $E(Y_i^0 \mid D_i = 1)$. $E(Y_i^0 \mid D_i = 1) - E(Y_i^0 \mid D_i = 0)$ indicates the extent of selection bias that arises when the ATE is used to examine the impact of a treatment in non-experimental studies. Therefore, given the non-random participation in agricultural extension, using Equation (8) to estimate the impacts of agricultural extension would yield biased estimators (*i.e.*, due to selection bias). The basic objective of the impact analysis is to find ways to make the selection bias zero ($E(Y_i^0 \mid D_i = 1) - E(Y_i^0 \mid D_i = 0) = 0$) so that the ATT=ATE. The PSM model can be employed to account for this selection bias.

The validity of the PSM method depends on two conditions: (1) the assumption of unconfoundedness or conditional independence (CIA); and (2) the assumption of common support (CSA). The CIA assumption states that given a set of observable covariates X, the respective treatment outcomes Y_i^1, Y_i^0 are independent of the actual participation status D. In notation, as follows:

$$(Y_i^1, Y_i^0) \perp P / X \tag{9}$$

Hence, after adjusting for observable differences, the mean of the potential outcome is the same for $D = 1$ and $D = 0$ ($E(Y_i^0 \mid D_i = 1) = E(Y_i^0 \mid D_i = 0)$). The CIA assumption permits the use of matched non-participating farms to measure how the group of participating farms would have performed had they not participated. Under the CIA, the propensity score in this study's context, which can be defined as the conditional probability that a farmer will participate in an agricultural extension program, given its pre-participation characteristic, is given as follows:

$$p(X) = \Pr(D = 1 | X) = E(D | X); p(X) = F\{h(Xi)\} \tag{10}$$

where $F\{\cdot\}$ can be the normal or logistic cumulative distribution and X is a vector of pre-treatment characteristics.

On the other hand, the CSA assumption rules out the phenomenon of perfect predictability by ensuring that every individual has a positive probability of either being a participant or a non-participant in an agricultural extension program. The CSA can be expressed as follows:

$$0 < \Pr(D = 1 | X) < 1 \tag{11}$$

Under the assumptions of CIA and CSA, the ATT effect can then be estimated as follows:

$$\begin{aligned} ATT &= E(Y_i^1 \mid D_i = 1) - E(Y_i^0 \mid D_i = 1) \\ &= E((Y_i^1 - Y_i^0) \mid D_i = 1)) \\ &= E\{E[(Y_i^1 - Y_i^0) \mid D_i = 1, p(X)]\} \\ &= E\{E[(Y_i^1 \mid D_i = 1, p(X)] - E[(Y_i^0 \mid D_i = 0, p(X)] \mid D_i = 1\} \end{aligned} \tag{12}$$

2.3.2. Matching Algorithm

Various matching algorithms are available to match participants with non-participants of similar propensity scores, depending on the distribution of the covariates in the matched treatment and control groups. In all matching algorithms, each treated individual i is paired with some group of comparable non-treated individuals j and then the outcome of the treated individual i, Y_i is linked with the weighted outcomes of his neighbors j in the comparison (control) group. Asymptotically, all matching methods should yield the same results. However, in practice, there are trade-offs in terms of bias and efficiency with each method [27]. The most commonly used approaches are nearest neighbor matching (NNM), kernel-based matching (KBM), and radius caliper matching (RM) [28]. The NNM involves choosing individuals from the participants and non-participants that are closest in terms of propensity scores as matching partners. It is usually applied with replacement in the control groups. In the KBM, all treated subjects are matched with a weighted average of all controls, using weights that are inversely proportional to the distance between the propensity scores of treated and comparison groups.

RM uses a tolerance level on the maximum propensity score distance between a subject in the treatment group and all individuals in the control group who are within that distance.

2.3.3. Matching Quality

Because the main purpose of PSM is to reduce selection bias by increasing the balance between the participants and non-participants [29], there should be no systematic differences in the distribution and overlap of covariates between the two groups after matching. It is important to check if the matching procedure is able to balance the distribution of the relevant variables across groups of participants and non-participants. This balancing test is normally required after matching to ascertain whether the differences in the covariates in the two matched sample groups have been eliminated, in which case, the matched comparison group can be considered plausibly counterfactual [20].

There are several covariate-balancing tests can be used to test the balance of the PSM results. In this study, we used the following methods to check the balance of the scores and covariates. First, we calculated the standardized bias before and after matching and checked for a significant difference in the covariates of both groups using a two-sample t-test. After matching, there should be no significant differences [30]. Secondly, we run a logit model using the after-matching sample to compare the pseudo-R^2 with the R^2 obtained from the logit estimation using the before-matching sample. After matching, there should be no systematic differences in the distribution of covariates between both groups, so the low value of a pseudo R^2 indicates that the balancing property is satisfied [31]. Finally, the balancing property was checked using the mean absolute standardized bias (MASB) between participants with non-participants, as suggested by Rosenbaum and Rubin [32], who recommend that a standardized difference of greater than 20% should be considered too large and an indicator that the matching process has failed.

2.3.4. Sensitivity Test

Despite the fact that PSM tries to compare the difference between the outcome variables of participants with non-participants with similar inherent characteristics, it cannot correct unobservable bias because PSM only controls for selection bias that is specifically due to observable variables ("selection on observables"). If there are unobserved variables that simultaneously affect the participation decision and the outcome variables, a "hidden bias" or "selection on unobservables" bias might arise and the PSM estimator may no longer be consistent. There is the need to check for sensitivity of the ATT to hidden bias after matching. Rosenbaum [30] has suggested the use of a sensitivity analysis called bounding approach to address this problem. The purpose of the sensitivity analysis is to ask whether inferences about participation effects may be changed by unobserved variables. The sensitivity analysis involves calculating upper and lower bounds with a Wilcoxon sign-rank test to test the null hypothesis of no participation effect for different hypothesized values of unobserved selection bias [33].

3. Data and Description Statistics

3.1. Sampling Procedure and Data

The data used for this paper were collected in a nearly nationally representative household survey in seven provinces of rural China, and the collection took place between January and March 2013. A three-stage stratified random-sampling design was chosen to ensure the representativeness of the sample. First, seven provinces were selected from China's major agro-ecological zones from a list of provinces arranged in descending order based on their gross value of industrial outputs (GVIO). The GVIO was used on the basis of the conclusion from [34] that the GVIO is one of the best predictors of the standard of living and development potential and is often more reliable than the net rural per capita income. The seven representative provinces included: Jiangsu, representing southeastern coastal rice production areas (Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong and Hainan); Shandong and Henan, representing northern rice production areas (Beijing, Tianjin, Hebei, Shanxi, Shandong and Henan); Sichuan, representing southwestern rice production areas (Sichuan, Chongqing, Guizhou, Guangxi, Yunnan and Tibet); Heilongjiang, representing northeastern rice production areas (Jilin, Liaoning, Heilongjiang and Inner Mongolia); and Hebei and Jiangxi, representing the central rice production areas (Anhui, Hubei, Jiangxi and Hunan). Second, in each selected province, three counties were randomly selected, one from each quintile of a list of counties arranged in descending order of GVIO. Third, within each selected county, three villages were chosen. Finally, twenty rice production households were then randomly sampled from a list of farming families in each village. As a result, a total of 1250 rice production households in 63 villages from 21 counties were surveyed using a standardized survey instrument.

The survey instrument was a closed-ended questionnaire that was modified from the baseline survey instrument. It was field-tested during a three-day training exercise with the enumerators and local researchers in each of the seven provinces. Data were checked using a data-cleaning syntax that checked for errors. Data cleaning was then performed at the country level by data assistants. The household survey used a structured questionnaire to collect data from the selected households on the demographic characteristics of the household, farm-level characteristics, individual features, farmer participation in agricultural extension programs, as well as farmer nutrient management behavior. In addition to the household survey, we also conducted a village survey to collect valuable information about the socio-economic characteristics and the agricultural extension program characteristics of the village.

3.2. Variable Selection

The implementation of matching requires the choice of a set of variables that credibly satisfy the assumption of unconfoundedness. The choice of covariates to be included in the first step (propensity score estimation) was an issue. Heckman *et al.* [21] indicated that omitting important variables will increase the bias in the resulting estimation. Bryon *et al.* [35] noted that including extraneous variables in the participation model would reduce the likelihood of finding common support. In principle, only variables that simultaneously influence the choice to participate in an agricultural extension program and the outcomes of participation, which are not affected by participation, should be included in the PSM when matching is performed [27]. Meanwhile, the choice of variables should be guided by previous research, economic theory, and the institutional setting within which the treatment and outcomes are measured. Under those principles, the variables employed in this study can be divided into three groups: the household characteristics (age, education, farming experience, risk attitude, extension contact, village leader, household income, off-farm income ratio, and distance to the nearest fertilizer shop); farm characteristics (farm size and soil quality) and village characteristics (extent of agricultural extension participation, village income and off-farm income ratio).

3.3. Summary Statistics

3.3.1. Summary Statistics of Independent Variables

Table 1 presents the definitions and differences in the characteristics of participants and non-participants with their t-values. The t-values indicate that there are significant differences in some of the variables used in the empirical analysis. Specifically, the participants were younger and were closer to the nearest fertilizer shop than non-participants. However, the education level, risk attitude, proportion of village leaders, farm size, soil quality and extent of agricultural extension participation in their village were all significantly higher factors for participants than for non-participants. The differences in the mean characteristics between participants and the non-participants that could have affected participation indicated a potential source of bias, hence, the need for matching and selection bias tests.

Table 1. Variables definition and differences in means of participants and non-participants.

Variables	Description	Participants (N = 396)		Non-participants (N = 854)		T-test
		Mean	SE	Mean	SE	
Household characteristics						
Age of household head	Year	45.90	9.43	51.70	9.94	0.055 **
Education of household head	1 = 0 year; 2 = less than 6 years; 3 = 6–9 years; 4= 9–12 years; 5= more than 12 years	2.97	0.91	2.62	0.90	0.032 **
Farming experience of household head	1 = less than 3 years; 2 = 3–10 years; 3 = 10–15 years; 4 = more than 15 years	3.26	1.03	3.22	0.93	0.174
Risk attitude of household head	1 = risk aversion; 2 = risk neutrality; 3 = risk loving	1.50	0.85	1.39	0.73	0.052 **
Extension contact	Number of household head's contact with the agricultural extension agent one year	3.03	2.88	2.30	2.77	0.001 ***
Village leader dummy	1 = the household head is a village leader, 0 = no	0.22	0.12	0.12	0.11	0.003 ***
Household income	Ln (household income)	10.76	0.84	10.64	0.87	0.231
Off-farm income ratio	The proportion of off-farm income to the total income (%)	54.31	34.04	54.52	32.03	0.127
Distance to the nearest fertilizer shop	Kilometers	3.00	3.38	4.98	4.85	0.002 ***
Farm characteristics						
Farm size	Ha	0.31	0.45	0.27	0.37	0.012 **
Soil quality	1 = poor; 2 = moderate; 3 = good	2.25	0.70	1.98	0.47	0.022 **

Table 1. *Cont.*

Variables	Description	Participants (N = 396)		Non-participants (N = 854)		T-test
		Mean	SE	Mean	SE	
Village characteristics						
Extent of village agricultural extension participation	The proportion of agricultural extension participants in village (%)	35.23	18.15	25.17	18.34	0.003 ***
Village income	Ln (village income)	10.68	0.57	10.57	0.62	0.256
Village off-farm income ratio	The proportion of off-farm income to the total income in village (%)	41.54	23.25	39.27	22.58	0.651

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10%, respectively.

3.3.2. Summary Statistics of Dependent Variables

In accordance with previous studies, farmer nutrient management behavior is measured in terms of the total amount of fertilizer used, the total amount of inorganic fertilizer used, the percentage of organic fertilizer used and the percentage of soil-testing-based fertilizer used [10,36].

Table 2 reports the nutrient management behavior of participants and non-participants in rice production. The nutrient management behavior appears to be more rational among the participants. First, participating farmers used much less fertilizer and inorganic fertilizer than non-participating farmers. Non-participating farmers applied an average of 717 kg ha^{-1} of fertilizer and 642 kg ha^{-1} of inorganic fertilizer, which was more than 10.648% and 19.109% of participating farmers, respectively. Second, the percentages of organic fertilizer used and soil-testing-based fertilizer used by participating farmers were much higher than those of non-participating farmers. For non-participating farmers, the percentages of organic fertilizer used and soil-testing-based fertilizer used were 6.834% and 3.626%, which were lower than the corresponding amounts of 3.660% and 2.701% used by participating farmers.

Table 2. Nutrient management behavior of participants and non-participants.

Nutrient management behavior	Participants	Non-participants	Differences
The total amount of fertilizer used (kg ha^{-1})	648	717	−69
The total amount of inorganic fertilizer used (kg ha^{-1})	539	642	−103
The percentage of organic fertilizer used (%)	10.494	6.834	3.660
The percentage of soil-testing-based fertilizer used (%)	6.327	3.626	2.701

The unconditional summary statistics in the above tables generally suggest that agricultural extension may have a role in improving farmer nutrient management behavior, but because agricultural extension participation is endogenous, a simple comparison of the nutrient management behavior indicators of participants and non-participants has no causal interpretation. That is, the above differences may not be the result of agricultural extension but instead may be due to other factors. Therefore, we need to use a PSM method to control for this self-selection problem to test the impact of agricultural extension participation on farmer nutrient management behavior.

4. Results and Discussion

In this section, we outline the common steps used to implement the PSM method. First, a probability model for participation in agricultural extension programs is estimated to calculate the probability (or propensity scores) of participation for each observation. In the second step, each participant is matched to a non-participant with a similar propensity score to estimate the ATT.

4.1. Factors That Affect Participation in Agricultural Extension

The factors that affect the decision to participate in agricultural extension programs are estimated using a logit model. Table 3 presents the results. The last column of Table 3 indicates changes in the probability of participation in agricultural extension programs given one unit of change in the explanatory variables; these are computed from the means of all of the explanatory variables. The likelihood ratio statistics of −138.024 suggested that the estimated model is statistically significant at the 1% level and that the pseudo-R^2 value indicates that the equation explains 25.39% of the variance in decision-making about whether to participate in an agricultural extension program.

Table 3. Logit regression estimates of propensity scores for participation in agricultural extension programs.

Variable	Coefficient	Standard error	Marginal Probability (dy/dx)
Household characteristics			
Age of household head	−0.0262 **	0.0132	−0.0116
Education of household head	0.0895 ***	0.0318	0.0498
Farming experience of household head	0.0538	0.2346	0.0023
Risk attitude of household head	0.3291	0.1129	0.0554
Extension contact	0.0821 **	0.0321	0.0167
Village leader dummy	0.7214 ***	0.2211	0.1872
Household income	1.1137	0.6752	0.2901
Off-farm income ratio	−1.3840	0.8775	−0.3438
Distance to the nearest fertilizer shop	−0.2513	0.0667	−0.0624
Farm characteristics			
Farm size	0.4251 **	0.1982	0.8520
Soil quality	−0.3158	0.3298	−0.0785
Village characteristics			
Extent of village agricultural extension participation	0.0568 ***	0.0081	0.0125
Village income	1.1253	0.9932	1.0231
Village off-farm income ratio	0.8782	0.8531	0.3453
Constant	−0.4105	2.8726	-
Log likelihood = −138.024; Pseudo R^2 = 0.2539; Prob > chi^2 = 0.000; Number of observations = 1250			

Note: (1) ***, **, and * indicate statistical significance at 1%, 5% and 10%, respectively; (2) The standard errors of the coefficients are estimated from bootstrap method with 1000 replications.

The results indicates that older farmers were less likely to participate in agricultural extension programs, whereas farmers that are more educated have a higher probability of participation. As expected, farmers that have more contact with agricultural extension agents are more likely to participate in agricultural extension programs. Being a village leader and having larger farm size also increased the probability of agricultural extension participation. The higher the proportion of agricultural extension participants in a village, the more likely farmers are to participate in agricultural extension programs.

4.2. Treatment Effects of the PSM Methods

The results modeling the impact of agricultural extension participation on farmer nutrient management behavior with KBM, RM and NNM are presented in Table 4. The three matching methods indicate that participation in agricultural extension programs has a positive impact on farmer nutrient management behavior.

The impact of agricultural extension participation on reducing fertilizer use and inorganic fertilizer use are positive and significant for all the matching algorithms. For the amount of fertilizer used, the ATT ranges from 11 to 24 kg ha^{-1}, implying that on average participants used 11 to 24 kg ha^{-1} less fertilizer than matched non-participants, and/or the amount of inorganic fertilizer used ranges from 10 to 18 kg ha^{-1}.

Agricultural extension participation also led to clear and significant improvement in organic fertilizer use and soil-testing-based fertilizer use. Farmers that participated in agricultural extension programs improved their percentage of organic fertilizer use by 1.008% to 1.705%. They also had a higher percentage of soil-testing-based fertilizer use than non-participants by an average score of 1.096% and 1.173%, respectively.

However, although agricultural extension participation has an impact on rationalizing farmer nutrient management behavior, this impact is trivial. Based on our study, participating farmers' total fertilizer use was reduced by only 1.7% to 3.7%, and their inorganic fertilizer use is reduced by only 1.9% to 3.3%. The improved percentage of organic fertilizer use and soil-testing-based fertilizer use due to agricultural extension participation are also small, ranging from 1.008% to 1.173%. The reasons for this are as follows: first, there are many complex barriers to effective knowledge and technology transfer to farmers in China. Most of the more than 200 million farmers in China are poorly educated, are relatively old, and operate very small holdings (an average 0.1–0.5 ha of agricultural land per farm) [11]; second, China has lacked a wide-reaching and functional extension system. According to one report, there were only 11 technicians providing services for 20,000 farmers in one county; at the township level, the extension personnel, if any, have become fertilizer salesmen or have become engaged in other unrelated activities (e.g., family planning) [15]; third, the extension system in China generally takes a top-down approach, determining what technologies should be transferred at the central, provincial or county level without the sufficient involvement of local farmers [13,36]; fourth, increasing agricultural production and food security have been the primary objectives of the agricultural extension system. Extension officers usually only promote programs intended to increase crop yields, as do most governmental incentives [37]. However, since the end of the 2000s, government policies have broadened to include, not only food security, but also environmental sustainability. For example, in 2005 the Ministry of Agriculture began a soil- and plant-testing program called the National Soil-Testing and

Fertilizer-Recommendation Program (STFR). By 2009, more than 2500 counties were involved and had received 1.5 billion Yuan of financial support from the central government to establish soil-testing laboratories and demonstrate the use of soil-testing and fertilizer recommendations for a diverse range of cropping systems. However, agricultural bureaus lack the knowledge, trained staff, and instruments (e.g., taxes and subsidies, regulatory authority, extension services, education and demonstration, and pollution standards) to implement such a policy with the concurrent goals of environmental sustainability and food security [11].

Table 4. Estimates of the average treatment effect on treated (ATT).

Outcome variable	Matching algorithm	Treated	Controls	ATT	T-stat
The total amount of fertilizer used (kg ha^{-1})	Kernel-based matching	648	672	−24	−1.897 *
	Radius caliper matching	648	665	−17	−2.012 **
	Nearest neighbor matching	648	659	−11	−2.134 **
The total amount of inorganic fertilizer used (kg ha^{-1})	Kernel-based matching	539	557	−18	−1.954 *
	Radius caliper matching	539	549	−10	−1.764 *
	Nearest neighbor matching	537	553	−16	2.894 ***
The percentage of organic fertilizer used (%)	Kernel-based matching	10.494	9.355	1.139	1.765 *
	Radius caliper matching	10.494	8.789	1.705	1.974 **
	Nearest neighbor matching	10.329	9.321	1.008	2.023 **
The percentage of soil-testing-based fertilizer used (%)	Kernel-based matching	6.327	5.231	1.096	2.248 **
	Radius caliper matching	6.327	5.218	1.109	1.836 *
	Nearest neighbor matching	6.327	5.154	1.173	2.113 **

Note: (1) ***, **, * denote statistical significance at the 1%, 5% and 10%, respectively; (2) T-values are calculated using bootstrap with 1000 repetitions.

To gain further understanding of the impact of agricultural extension participation on different groups of participants, we also examined the differential impact of participation by dividing households into different categories based on education level, risk attitude, initial application level and farm size. The stratification was made based on matched samples obtained from the nearest neighbor-matching estimator. (Results are reported in Tables 5–8.)

As observed in Table 5, the impact of participation on total fertilizer use and inorganic fertilizer use decrease with educational level, while the relationship between participation and organic fertilizer use and soil-testing-based fertilizer use are positive. This is consistent with the expectation that better educated farmers are more adept at acquiring and processing information from various sources, and then adopting and implementing recommendations and solutions relevant to their specific problems [38].

Table 5. Differential impact by education level.

Category	Outcome variable	ATT	T-stat
Low (0–6 years)	The total amount of fertilizer used (kg ha^{-1})	−11.21	−1.978 **
	The total amount of inorganic fertilizer used (kg ha^{-1})	−9.87	−2.321 **
	The percentage of organic fertilizer used (%)	1.012	1.856 *
	The percentage of soil-testing-based fertilizer used (%)	0.098	1.985 **

Table 5. *Cont.*

Category	Outcome variable	ATT	T-stat
Middle (6–9 years)	The total amount of fertilizer used (kg ha^{-1})	−13.45	−1.765 *
	The total amount of inorganic fertilizer used (kg ha^{-1})	−10.34	−1.995 **
	The percentage of organic fertilizer used (%)	1.213	2.012 **
	The percentage of soil-testing-based fertilizer used (%)	1.011	1.764 *
High (more than 9 years)	The total amount of fertilizer used (kg ha^{-1})	−15.76	−2.679 ***
	The total amount of inorganic fertilizer used (kg ha^{-1})	−13.25	−2.114 **
	The percentage of organic fertilizer used (%)	1.432	2.789 ***
	The percentage of soil-testing-based fertilizer used (%)	1.163	2.065 **

Note: (1) ***, **, * denote statistical significance at the 1%, 5% and 10%, respectively; (2) T-values are calculated using bootstrap with 1000 repetitions.

Table 6 presents results for the causal impacts of participation on nutrient management behavior for different categories of risk attitude. The results generally reveal that the participation of agricultural extension exerts a positive and statistically significant impact on nutrient management behavior among the risk-loving farmers and risk-neutrality farmers, but insignificant effects on the risk-aversion farmers. It may be that risk aversion leads farmers to want to avoid the possibility of applying too little fertilizer, and are less concerned about applying too much fertilizer. Given that farmers in China, like rural households in many developing countries, have limited access to formal insurance and credit markets, they are generally risk-averse and more risk aversion can lead to more intensive fertilizer use, providing crop insurance would be a beneficiary policy to help alleviate farmers' fertilizer use.

Table 6. Differential impact by risk attitude.

Category	Outcome variable	ATT	T-stat
Risk aversion	The total amount of fertilizer used (kg ha^{-1})	−9.34	−1.045
	The total amount of inorganic fertilizer used (kg ha^{-1})	−8.47	−1.326
	The percentage of organic fertilizer used (%)	0.078	1.543
	The percentage of soil-testing-based fertilizer used (%)	0.094	1.456
Risk neutrality	The total amount of fertilizer used (kg ha^{-1})	−12.64	−2.065 **
	The total amount of inorganic fertilizer used (kg ha^{-1})	−11.78	−1.978 **
	The percentage of organic fertilizer used (%)	1.117	2.114 **
	The percentage of soil-testing-based fertilizer used (%)	1.014	2.064 **
Risk loving	The total amount of fertilizer used (kg ha^{-1})	−16.56	−2.896 ***
	The total amount of inorganic fertilizer used (kg ha^{-1})	−13.43	−2.015 **
	The percentage of organic fertilizer used (%)	1.332	1.986 **
	The percentage of soil-testing-based fertilizer used (%)	1.432	2.234 **

Note: (1) ***, **, * denote statistical significance at the 1%, 5% and 10%, respectively; (2) T-values are calculated using bootstrap with 1000 repetitions.

The relationship between participation and initial application level are shown in Table 7. The results generally reveal that within the different initial application level groups, the impacts of participation on nutrient management behavior are all very trivial. The reason for this result may be that farmers in China had been overusing fertilizer in the past and they are becoming too used to relying on chemical fertilizer. As a result, farmers become locked into "unsustainable" agricultural systems once fertilizers are adopted. As Tisdell [39] demonstrates, when chemical agricultural systems are adopted, agricultural yields or returns become dependent on them despite the very high costs, and thus impose an "economic barrier" to switching to organic systems. In short, agricultural practices tend to become "inclined towards" such systems once they are adopted despite being unsustainable.

Table 7. Differential impact by initial application level.

Category	Outcome variable	ATT	T-stat
Low	The total amount of fertilizer used (kg ha^{-1})	−7.38	−1.972 **
	The total amount of inorganic fertilizer used (kg ha^{-1})	−5.34	−1.718 *
	The percentage of organic fertilizer used (%)	0.076	2.002 **
	The percentage of soil-testing-based fertilizer used (%)	0.087	1.684 *
Middle	The total amount of fertilizer used (kg ha^{-1})	−7.35	−2.124 **
	The total amount of inorganic fertilizer used (kg ha^{-1})	−6.93	−1.765 *
	The percentage of organic fertilizer used (%)	0.098	2.321 **
	The percentage of soil-testing-based fertilizer used (%)	1.012	1.804 *
High	The total amount of fertilizer used (kg ha^{-1})	−10.23	−1.865 *
	The total amount of inorganic fertilizer used (kg ha^{-1})	−7.45	−2.327 **
	The percentage of organic fertilizer used (%)	0.096	1.911 *
	The percentage of soil-testing-based fertilizer used (%)	1.112	2.132 **

Note: (1) ***, **, * denote statistical significance at the 1%, 5% and 10%, respectively; (2) T-values are calculated using bootstrap with 1000 repetitions.

Results from the causal impacts of participation on nutrient management behavior for different categories of farm size are presented in Table 8. It is significant to note that agricultural extension participation exerts a positive and statistically significant impact on nutrient management behavior among the medium and large farmers, but insignificant effects on the small-scale farmers. This result is consistent with Zhou *et al.* [40], who found an inverse relationship between farm size and fertilizer intensity in a study in Hebei Province, indicating that smaller farms are more likely to have high intensities. The reason for the insignificant effects of the small-scale farmers may be that farmers with less farm land will find it more difficult to spread the risks across family plots and, thus, could possibly use fertilizer more intensively to stabilize the crop yields.

Table 8. Differential impact by farm size.

Category	Outcome variable	ATT	T-stat
Small	The total amount of fertilizer used (kg ha^{-1})	−10.21	−1.214
	The total amount of inorganic fertilizer used (kg ha^{-1})	−9.32	−1.431
	The percentage of organic fertilizer used (%)	0.092	1.614
	The percentage of soil-testing-based fertilizer used (%)	0.086	1.542
Medium	The total amount of fertilizer used (kg ha^{-1})	−12.56	−2.124 **
	The total amount of inorganic fertilizer used (kg ha^{-1})	−11.45	−2.247 **
	The percentage of organic fertilizer used (%)	1.034	1.986 **
	The percentage of soil-testing-based fertilizer used (%)	1.112	2.578 ***

Table 8. *Cont.*

Category	Outcome variable	ATT	T-stat
Large	The total amount of fertilizer used (kg ha^{-1})	−15.98	−2.797 ***
	The total amount of inorganic fertilizer used (kg ha^{-1})	−14.43	−2.015 **
	The percentage of organic fertilizer used (%)	1.332	2.028 **
	The percentage of soil-testing-based fertilizer used (%)	1.213	2.456 **

Note: (1) ***, **, * denote statistical significance at the1%, 5% and 10%, respectively; (2) T-values are calculated using bootstrap with 1000 repetitions.

4.3. Assessing the Quality of the Matching Process

The matching process is checked to determine whether it balances the distribution of the relevant covariates in both the treatment and control groups using different methods. The results of the covariate-balancing tests are presented in Tables 9 and 10.

First, the propensity score test indicates a significant reduction in bias after matching, and most importantly, there are no significant differences in matched non-participants and participants for any of the covariates (Table 9).

Table 9. Tests for selection bias after matching.

Variable	Matched sample		Bias		T-test *p*-value
	Treated (N = 396)	Control (N = 854)	% Bias	% Bias reduction	
Household characteristics					
Age of household head	46.21	49.98	−36.35	46.21	0.521
Education of household head	2.89	2.56	38.79	5.71%	0.358
Farming experience of household head	3.57	3.54	3.50	25.00%	0.172
Risk attitude of household head	1.49	1.44	6.32	54.55%	0.616
Extension contact	3.25	2.65	20.66	77.62%	0.216
Village leader dummy	0.22	0.13	33.57	3.01%	0.238
Household income	10.83	10.78	5.74	−38.78%	0.228
Off-farm income ratio	55.98	56.04	−20.48	14.97%	0.172
Distance to the nearest fertilizer shop	2.97	4.86	−9.80	36.03%	0.425
Farm characteristics					
Farm size	0.34	0.31	15.86	22.81%	0.106
Soil quality	2.18	2.14	1.62	85.19%	0.273
Village characteristics					
Extent of village agricultural extension participation	36.32	26.61	54.55	3.48%	0.345
Village income	10.64	10.56	2.99	27.27%	0.772
Village off-farm income ratio	39.87	38.95	6.34	59.47%	0.298

Second, there is a substantial reduction in bias as a consequence of matching. The estimates indicate that the standardized mean bias before matching is 28.71%, whereas the standardized mean bias after matching is reduced to between 6.79% and 13.65%. The percentage reductions in the absolute bias are 65.62%, 76.35% and 52.46% with KBM, RM and NNM matching methods, respectively. Because the percentage reduction in bias by all three matching methods is greater than 20%, a value recommended by Rosenbaum and Rubin [32] as a sufficiently large enough reduction in standardized bias, it is determined that the matching substantially reduced the selection bias. Similarly, the pseudo-R^2 of the estimated logit model was high before matching and low afterwards for all matching algorithms. The *p*-value of the likelihood ratio test was always rejected after matching, whereas it was never rejected at any significance level before matching, suggesting that there is no systematic difference in the distribution of covariates between participants and non-participants after matching (Table 10).

Table 10. Statistical tests to evaluate the matching.

Matching algorithm	Mean bias		% |bias| reduction	Pseudo-R^2		*p*-value of LR	
	Before matching	After matching		Unmatched	Matched	Unmatched	Matched
Kernel-based matching	28.71	9.87	65.62	0.2539	0.0923	0.000	0.432
Radius caliper matching	28.71	6.79	76.35	0.2539	0.0897	0.000	0.654
Nearest neighbor matching	28.71	13.65	52.46	0.2539	0.1125	0.000	0.786

4.4. Testing for Hidden Bias with Sensitivity Analysis

Might endogeneity drive our results? As noted above, the effectiveness of our matching estimators in controlling for selection bias are dependent on the untestable identifying assumption that we are able to observe confounding variables that simultaneously affect farmers' decisions to participate in agricultural extension programs and to adopt or not to adopt the nutrient management practices that serve as our outcome variables. That is, we essentially assume that endogeneity is not a problem [17]. We calculate Rosenbaum bounds to check the sensitivity of our results with the failure of this assumption. Given that the sensitivity analysis of insignificant effects is not meaningful, the Rosenbaum bounds were calculated only for the treatment effects that are significantly different from zero [41]. As Duvendack and Palmer-Jones [42], and DiPrete and Gangl [43] noted, if the critical value is less than two, one may assert that the likelihood of such unobserved characteristic is relatively high; therefore, the estimated impact is rather sensitive to the existence of unobservables. As shown in Table 11, in our results, the lowest critical value of γ is 2.08, whereas the largest critical value of γ is 4.59. Therefore, our sensitivity tests suggest that even large amounts of unobserved heterogeneity would not alter the inference of the estimated effects. In other words, endogeneity is unlikely to drive our results.

Table 11. Sensitivity analysis with Rosenbaum bounds.

Matching algorithm	Outcome Variable	Critical level of hidden bias(γ)
Kernel-based matching	The total amount of fertilizer used (kg ha^{-1})	2.08–2.12
	The total amount of inorganic fertilizer used (kg ha^{-1})	3.15–3.23
	The percentage of organic fertilizer used (%)	2.65–2.72
	The percentage of soil-testing-based fertilizer used (%)	2.78–2.86
Radius caliper matching	The total amount of fertilizer used (kg ha^{-1})	2.21–2.32
	The total amount of inorganic fertilizer used (kg ha^{-1})	3.04–3.11
	The percentage of organic fertilizer used (%)	2.26–2.34
	The percentage of soil-testing-based fertilizer used (%)	3.21–3.56

Table 11. *Cont.*

Matching algorithm	Outcome Variable	Critical level of hidden bias(γ)
Nearest neighbor matching	The total amount of fertilizer used (kg ha^{-1})	2.48–2.65
	The total amount of inorganic fertilizer used (kg ha^{-1})	4.32–4.59
	The percentage of organic fertilizer used (%)	3.15–3.26
	The percentage of soil-testing-based fertilizer used (%)	2.48–2.52

5. Conclusions

Agricultural nutrients play a critical role in food production and human nutrition and health in China. However, the oversupply of nutrients has resulted in serious environmental problems. Managing agricultural nutrients to provide a safe and secure food supply while protecting the environment remains one of the great challenges in 21st-century China. Providing knowledge and information through agricultural extension services to farmers is essential for nutrient management. Therefore, this study examined participation in agricultural extension programs on farmer nutrient management behavior based on a nearly nationally representative household survey in seven provinces of rural China. Given the non-experimental nature of the data used in the analysis, the causal impact of agricultural extension participation is estimated by utilizing a PSM method. This helps in estimating the true effect of agricultural extension participation by controlling for the role of selection bias problems.

Three main conclusions can be drawn from the results of this study. First, the group of farmers that participated in agricultural extension programs has systematically different characteristics than the group of farmers that did not participate. These differences represent sources of variation between the two groups that the estimation of an OLS model, including a dummy variable for participation, cannot take into account. Second, the empirical results from the PSM analysis show that agricultural extension participation has a positive impact on rationalizing farmer nutrient management behavior; however, the impact is trivial. Compared with non-participating farmers, the reduced ratio of total fertilizer use and inorganic fertilizer use by participating farmers are only 1.7% to 3.7%, and the improved ratio of organic fertilizer use and soil-testing-based fertilizer use are only 1.008% to 1.173%. Third, we found interesting results from differential impacts of participation, based on education level, risk attitude, initial application level and farm size. The causal impacts of participation on nutrient management behavior tend to be higher for more educated, risk-loving and larger-scale farmers.

This study has important policy implications. First, for agricultural extension to have a long-term and more significant impact on farmer nutrient management behavior, more training efforts or other methods, such as the participatory approach to farming education during the entire crop season, are needed. However, how to implement improved nutrient management practices on hundreds of millions of Chinese farms through extension is a major challenge to the agricultural extension system. The development of more effective methods for delivering information to farmers is essential. Working through Farmer Professional Associations and using Farmer Field Schools are obvious steps forward. Meanwhile, given that the causal impacts of participation on nutrient management behavior are higher for more educated, risk-loving and larger-scale farmers, targeting these farmers with agricultural extension programs will have great demonstration effects on other farmers. Second, a shift in the focus of national policies from merely food security to an integrated approach that emphasizes food security, the efficient use of resources, and environmentally sound production and consumption are highly desirable. Third, governmental support of agriculture should be redirected. We recommend abandoning indirect fertilizer subsidies and increasing direct support to farmers who adopt environmentally friendly nutrient management practices.

While this study has made significant advancements in knowledge about the impact of agricultural extension participation on farmer nutrient management behavior, it nevertheless has its limitations. That is, the effect of agricultural extension on the change in farmer nutrient management behavior may be seen a long time after the extension program. However, due to the lack of panel data, we can only rely on a cross-sectional data set to evaluate this impact, which may bias the estimated results of this study.

Acknowledgments

We would like to thank the financial support from National Natural Science Foundation of China (No.71303099), Technology Foundation of Jiangxi Education Department (No. GJJ13291), the Social Science Foundation of Jiangxi Province (No.13YJ50), Great National Social Science Fund Program (No.11&ZD155; No.12&ZD213) and the MOE Layout Foundation of Humanities and Social Sciences (No.11YJA790192).

Conflicts of Interest

The author declares no conflict of interest.

References

1. Galloway, J.N.; Townsend, A.R.; Erisman, J.W.; Bekunda, M.; Cai, Z.; Freney, J.R.; Martinelli, L.A.; Seitzinger, S.P.; Sutton, M.A. Transformation of the Nitrogen Cycle: Recent Trends, Questions, and Potential Solutions. *Science* **2008**, *320*, 889–892.
2. Erisman, J.W.; Sutton, M.A.; Galloway, J.; Klimont, Z.; Winiwarter, W. How a century of ammonia synthesis changed the world. *Nat. Geosci.* **2008**, *1*, 636–639.
3. Sayer, J.; Cassman, K.G. Agricultural innovation to protect the environment. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 8345–8348.
4. Liu, J.; Diamond, J. China's environment in a globalizing world. *Nature* **2005**, *435*, 1179–1186.
5. Zhang, F.; Chen, X.; Vitousek, P. Chinese agriculture: An experiment for the world. *Nature* **2013**, *497*, 33–35.
6. Peng, S.; Buresh, R.J.; Huang, J.; Zhong, X.; Zou, Y.; Yang, J.; Wang, G.; Liu, Y.; Hu, R.; Tang, Q.; *et al.* Improving nitrogen fertilization in rice by site-specific N management. A review. *Agron. Sustain. Dev.* **2010**, *30*, 649–656.
7. Ma, L.; Velthof, G.L.; Wang, F.H.; Qin, W.; Zhang, W.F.; Liu, Z.; Zhang, Y.; Wei, J.; Lesschen, J.P.; Ma, W.Q.; *et al.* Nitrogen and phosphorus use efficiencies and losses in the food chain in China at regional scales in 1980 and 2005. *Sci. Total Environ.* **2012**, *434*, 51–61.
8. Izaurralde, R.C.C.; Mcgill, W.B.; Rosenberg, N.J. Carbon Cost of Applying Nitrogen Fertilizer. *Science* **2000**, *288*, 811–812.

9. Zhu, Z.L.; Chen, D.L. Nitrogen fertilizer use in China—Contributions to food production, impacts on the environment and best management strategies. *Nutr. Cycl. Agroecosys.* **2002**, *63*, 117–127.
10. Huang, J.; Xiang, C.; Jia, X.; Hu, R. Impacts of training on farmers' nitrogen use in maize production in Shandong, China. *J. Soil Water Conserv.* **2012**, *67*, 321–327.
11. Ma, L.; Zhang, W.F.; Ma, W.Q.; Velthof, G.L.; Oenema, O.; Zhang, F.S. An analysis of developments and challenges in nutrient management in china. *J. Environ. Qual.* **2013**, *42*, 951–961.
12. Huang, J.; Hu, R.; Cao, J.; Rozelle, S. Training programs and in-the-field guidance to reduce China's overuse of fertilizer without hurting profitability. *J. Soil Water Conserv.* **2008**, *63*, 165–167.
13. Hu, R.; Cao, J.; Huang, J.; Peng, S.; Huang, J.; Zhong, X.; Zou, Y.; Yang, J.; Buresh, R.J. Farmer participatory testing of standard and modified site-specific nitrogen management for irrigated rice in China. *Agric. Syst.* **2007**, *94*, 331–340.
14. Cui, Z.; Zhang, F.; Miao, Y.; Sun, Q.; Li, F.; Chen, X.; Li, J.; Ye, Y.; Yang, Z.; Zhang, Q.; *et al.* Soil nitrate-N levels required for high yield maize production in the North China Plain. *Nutr. Cycl. Agroecosys.* **2008**, *82*, 187–196.
15. Li, Y.; Zhang, W.; Ma, L.; Huang, G.; Oenema, O.; Zhang, F.; Dou, Z. An Analysis of China's Fertilizer Policies: Impacts on the Industry, Food Security, and the Environment. *J. Environ. Qual.* **2013**, *42*, 972–981.
16. Jia, X.; Huang, J.; Xiang, C.; Hou, L.; Zhang, F.; Chen, X.; Cui, Z.; Bergmann, H. Farmer's Adoption of Improved Nitrogen Management Strategies in Maize Production in China: An Experimental Knowledge Training. *J. Integr. Agric.* **2013**, *12*, 364–373.
17. Blackman, A.; Naranjo, M.A. Does eco-certification have environmental benefits? Organic coffee in Costa Rica. *Ecol. Econ.* **2012**, *83*, 58–66.
18. Kassie, M.; Shiferaw, B.; Muricho, G. Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda. *World Dev.* **2011**, *39*, 1784–1795.
19. Gitonga, Z.M.; De Groote, H.; Kassie, M.; Tefera, T. Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. *Food Policy* **2013**, *43*, 44–55.
20. Ali, A.; Abdulai, A. The Adoption of Genetically Modified Cotton and Poverty Reduction in Pakistan. *J. Agric. Econ.* **2010**, *61*, 175–192.
21. Heckman, J.J.; Ichimura, H.; Todd, P.E. Matching As an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Rev. Econ. Stud.* **1997**, *64*, 605–654.
22. Dehejia, R.H.; Wahba, S. Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Rev. Econ. Stat.* **2002**, *84*, 151–161.
23. Smith, J.A.; Todd, P.E. Does matching overcome LaLonde's critique of nonexperimental estimators? *J. Econ.* **2005**, *125*, 305–353.
24. Imbens, G.W.; Wooldridge, J.M. Recent Developments in the Econometrics of Program Evaluation. *J. Econ. Lit.* **2009**, *47*, 5–86.
25. Ferraro, P.J.; Pattanayak, S.K. Money for Nothing? A Call for Empirical Evaluation of Biodiversity Conservation Investments. *PLoS Biol.* **2006**, *4*, e105, doi:10.1371/journal.pbio.0040105.
26. Rosenbaum, P.R.; Rubin, D.B. The central role of the propensity score in observational studies for causal effects. *Biometrika* **1983**, *70*, 41–55.

27. Caliendo, M.; Kopeinig, S. Some practical guidance for the implementation of propensity score matching. *J. Econ. Surv.* **2008**, *22*, 31–72.
28. Becker, S.O.; Ichino, A. Estimation of average treatment effects based on propensity scores. *Stata J.* **2002**, *2*, 358–377.
29. Lee, W.-S. Propensity score matching and variations on the balancing test. *Empir. Econ.* **2013**, *44*, 47–80.
30. Rosenbaum, P.R. *Observational Studies*; Springer: Berlin/Heidelberg, Germany, 2002.
31. Sianesi, B. An Evaluation of the Swedish System of Active Labor Market Programs in the 1990s. *Rev. Econ. Stat.* **2004**, *86*, 133–155.
32. Rosenbaum, P.R.; Rubin, D.B. Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *Am. Stat.* **1985**, *39*, 33–38.
33. Kassie, M.; Zikhali, P.; Pender, J.; Köhlin, G. The Economics of Sustainable Land Management Practices in the Ethiopian Highlands. *J. Agric. Econ.* **2010**, *61*, 605–627.
34. Rozelle, S. Stagnation without equity: patterns of growth and inequality in China's rural economy. *China J.* **1996**, *35*, 63–92.
35. Bryson, A.; Dorsett, R.; Purdon, S. The use of propensity score matching in the evaluation of active labour market policies. Available online: http://eprints.lse.ac.uk/4993/1/The_use_of_propensity_score_matching_in_the_evaluation_of_active_labour_market_policies.pdf (accessed on 22 September 2014).
36. Miao, Y.; Stewart, B.A.; Zhang, F. Long-term experiments for sustainable nutrient management in China. A review. *Agron. Sustain. Dev.* **2010**, *31*, 397–414.
37. Hu, R.; Yang, Z.; Kelly, P.; Huang, J. Agricultural extension system reform and agent time allocation in China. *China Econ. Rev.* **2009**, *20*, 303–315.
38. Mishra, A.K.; Wesley Nimon, R.; El-Osta, H.S. Is moral hazard good for the environment? Revenue insurance and chemical input use. *J. Environ. Manag.* **2005**, *74*, 11–20.
39. Tisdell, C. *Environmental Economics: Policies for Environmental Management and Sustainable Development*; Edward Elgar: Aldershot, UK, 1993.
40. Zhou, Y.; Yang, H.; Mosler, H.J.; Abbaspour, K.C. Factors Affecting Farmers Decisions on Fertilizer Use: A Case Study for the Chaobai Watershed in Northern China. *J. Sustain. Dev.* **2010**, *4*, 80–102.
41. Hujer, R.; Caliendo, M.; Thomsen, S.L. New evidence on the effects of job creation schemes in Germany—a matching approach with threefold heterogeneity. *Res. Econ.* **2004**, *58*, 257–302.
42. Duvendack, M.; Palmer-Jones, R. High noon for microfinance impact evaluations: Re-Investigating the evidence from Bangladesh. *J. Dev. Stud.* **2012**, *48*, 1864–1880.
43. DiPrete, T.A.; Gangl, M. Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on Matching Estimators and Instrumental Variables Estimation with Imperfect Instruments. *Sociol. Methodol.* **2004**, *34*, 271–310.