Improving smallholder farmer's soil nutrient management: the effect of science and technology backyards in the North China plain

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Abstract

Purpose – Soil nutrient management and fertilizer use by farmers are important for sustainable grain production. The authors examined the effect of an experimental agricultural extension program, the science and technology backyard, in promoting sustainable soil nutrient management in the North China Plain (NCP). The science and technology backyard integrates farmer field schools, field demonstrations, and case-to-case counselling to promote sustainable farming practices among rural smallholders.

Design/methodology/approach – The authors conducted a large-scale household survey of more than 2,000 rural smallholders. The authors used a multivariate regression analysis as the benchmark to assess the effect of the science-and-technology backyard on smallholder soil nutrient management. Furthermore, the authors used coarse exact matching (CEM) methods to control for potential bias due to self-selection and the (endogenous) switching regression approach as the main empirical analysis.

Findings – The results show that the science-and-technology backyard program increased smallholders' wheat yield by approximately 0.23 standard deviation; however, no significant increase in maize yield was observed. Regarding soil nutrient use efficiency, the authors found a significant improvement in smallholders' phosphorus and potassium use efficiencies for both wheat and maize production, and a significant improvement in nitrogen use efficiency for wheat production, but no significant improvement of nitrogen use efficiency for maize production.

Originality/value – This study evaluated a novel participatory agricultural extension model to improve soil nutrient management practices among smallholders. The integration of agronomists' scientific knowledge and smallholders' local contextual experiences could be an effective way to improve farmers' soil nutrient management. This study provides the first quantitative estimates based on rigorous impact assessment methods of this novel extension approach in rural China.

Keywords Agricultural extension, Soil nutrient management, Fertilizer use, Treatment effect, Rural China

Paper type Research paper

1. Introduction

There is growing concern in China regarding its environmental sustainability in food production (Norse and Ju, 2015). The demands for food in China pose significant challenges in food provision, especially with its increasing purchasing power. Continuous intensification (e.g. intensive use of chemical fertilizers) does not guarantee sustainable food provision (Kassie *et al.*, 2015). Chinese farmers use a substantially higher amount of fertilizer per hectare than farmers anywhere else in the world (FAO, 2017) [1]. The intensive use of chemical fertilizers has caused severe pollution of groundwater, rivers, and lakes (Qu *et al.*, 2011). However, China's agricultural production is still dominated by smallholder farming systems (Rapsomanikis, 2015) and is an important source of income for the smallholders. Meeting the increasing food demand and transforming it into sustainable food production has become an urgent challenge.

Early experiences show that agricultural extension can play a critical role in disseminating information and technology (Swanson, 2006a; Duflo *et al.*, 2008; Takahashi and Barrett, 2014). Its success was evidenced during the "*Green Revolution*," when public agricultural extension was delivered to millions of smallholders (Alston *et al.*, 2000; Swanson, 2006b; Van Braun, 2007). However, the central goal of agricultural extensions during the "*Green Revolution*" was to increase productivity (Swanson *et al.*, 2003), and most technologies introduced, such as chemical fertilizers, pesticides (Pimentel, 1996; Carvalho, 2006), and large-scale mechanization (Pingali, 2007), were less concerned about environmental sustainability.

Building a sustainable agricultural extension requires multiple innovations, including (1) productivity innovation, which ensures food security; (2) natural resource management innovation, which improves resource use efficiency and reduces environmental damage; and (3) institutional innovation, which guarantees sustainable operation of the extension system (Pretty *et al.*, 2011; Robinson *et al.*, 2015). In many developing countries, including China, the agricultural extension system is fragmented (Garfield *et al.*, 1996) and unaffordable for smallholders (Sulaiman and Sadamate, 2000) [2]. From the supply side, many privately funded agricultural extensions are persistent with a "*productivity-profit-orientation*" (Rivera,

1997). This has resulted in various unintended negative effects on environmental sustainability. From the users' perspective, the lack of information and low educational attainment among smallholders often limit their accessibility to advanced technologies (Feder *et al.*, 1985; Kassie *et al.*, 2013). The presence of the "know-do gap" further inhibits technology adoption (Udry, 1990; World Bank, 2008).

Given the wide advocacy of sustainable agricultural production and the hard realities of extension systems in most developing countries (Schut *et al.*, 2016), this paper presents an innovative solution that has been tested in China and outlines insights for the further development of agricultural extension. Specifically, we study an active participatory agricultural extension model, namely the "*Science and Technology Backyard*" (STB). The STB model was developed and implemented by a group of agronomists from the China Agricultural University in the North China Plain (NCP). It integrates farmer field schools, field demonstrations, and case-to-case counselling to promote sustainable agricultural production. In practice, STB is organized by experts (mostly agronomists and experts from other related disciplines) and postgraduate agronomy students who work jointly with local community smallholders. A recent paper by Zhang *et al.* (2016), published in *Nature*, provided a detailed description of the STB model in the field and a primary evaluation of the effects of STB on smallholders' agricultural production.

However, the evaluations by Zhang *et al.* (2016) suffer from several limitations. First, direct outcome comparisons between STB and non-STB villages might present a serious sample selection problem if the STB villages were not randomly selected (Imbens, 2004; Rosenbaum, 2010). In other words, if there was a confounding factor affecting both the outcome and participation in the STB program, the outcome comparison might overestimate (or underestimate) the true effect of STB. Second, the data used in Zhang *et al.* (2016) were primarily collected from 2011 to 2012, approximately two to three years after the establishment of the STB. Some previous studies found more significant effects of agricultural extension in the long term (Davis *et al.*, 2012), while other studies claim that the short-term effect will eventually fade out (Tripp *et al.*, 2005; Rejesus *et al.*, 2012). It would be interesting to examine the long-run effect of STB and compare it with other similar studies in other developing country contexts. In addition, the sample size of the control group (both smallholders from neighboring villages and control villages) in Zhang *et al.* (2016) was rather small, and there were limited comparisons of smallholder farming and farm-related characteristics. Inferences from this small sample comparison might lead to low statistical power.

In this study, we examined the long-term effects of STB on smallholder soil nutrient management using a quasi-experimental approach. We specifically focused on smallholder fertilizer use as the main practice in soil nutrient management. We conducted a large-scale household survey with 2,000 rural smallholders from 135 villages in early 2018 to assess the effect of the science-and-technology backyard on smallholder grain production and soil nutrient use efficiencies. We first ran a multivariate regression analysis as the benchmark analysis. Furthermore, to control for potential bias due to sample self-selection, we used both the coarse exact matching (CEM) method and the (endogenous) switching regression model to conduct the main empirical analysis. Additionally, we benchmark our study against farmer field school studies from other developing countries, discuss the limitations of STB practice, its potential improvement, and policy implications.

Our study contributes to the literature on the development of agricultural extensions to promote sustainable farming among smallholders in developing countries. First, China's agricultural extension has been a great success in transforming itself into a modern agricultural production system (Huang and Yang, 2017). However, its environmental sustainability remains a challenge. The practice of the STB program is of great value in providing more insight into reforming China's agricultural extension. Second, unlike the

conventional government-led extension program, STB is a public university-led extension program. It has integrated both up-to-date agronomic knowledge and local geo-climate contextual experiences carried out by university staff. Understanding the internal mechanism and its effectiveness can yield a strong policy implication, given that China outlined an ambitious target for achieving agricultural green development in its 19th National Congress of the Chinese Communist Party in 2017.

The remainder of this paper is organized as follows. In Section 2, we present the problem of smallholders' intensive use of chemical fertilizers in China and a brief description of the STB in the field. In Section 3, we present our research design regarding sampling, data collection, and the analytical approach used for quantitative analysis. We present the results in Section 4 and conclude the paper with an extensive discussion in Section 5.

2. Sustainable agricultural development in rural China
China's agricultural production has undergone several significant transformations since the 1980s (Yu and Zhao, 2009). The growth of agricultural productivity in China has primarily been achieved through continuous intensification. According to national statistics, China's grain production has increased at an annual rate of 20% since the early 1990s (NBS, 2012). However, the use of chemical fertilizers during the same time has increased at an annual rate of more than 30% (Wu *et al.*, 2018; Xu, 2020). Smallholders who cultivated less than 1 hectare of land consumed a substantial share of the increase in fertilizer use.

2.1 The intensive use of chemical fertilizers in China
The concern about the intensive use of chemical fertilizers was triggered by its significant negative impact on China's water system, in both surface and ground water. During the 1970s and the 1980s, the application of chemical fertilizers was largely nitrogen (N) fertilizers, followed by the addition of phosphorus (P) and potassium (K) when synthetic fertilizers were introduced (N-P-K, Fan *et al.*, 2012).

The large-scale intensive use of chemical fertilizers can be attributed to three factors. The first is political concerns over food self-sufficiency and national food security (Ghose, 2014; Wong and Huang, 2012). To ensure food self-sufficiency, promoting "*productivity-oriented*" agricultural development policies was the priority for a period of time (MoA, 2016). During this period, the use of chemical fertilizers was encouraged by agricultural extensions to achieve high yields. Second, with the continuous decentralization and privatization of agricultural extensions since the 1990s, many grassroots (village- and township-level) extensionists have become self-employed with agricultural extension reform and a decrease in public financial support (Qiao *et al.*, 1999; Hu *et al.*, 2004). According to some anecdotes, a substantial share of current agricultural input retailers is formal local extensionists (specializing in fertilizers and pesticides). Profit maximization and market share have become primary goals (Hu *et al.*, 2004). Third, many studies argue that the intensive use of chemical fertilizers is partially because smallholders are risk-averse (Chen *et al.*, 2018) and are misinformed (Huang *et al.*, 2012a) [3]. These studies often call for political and financial support from agricultural extension systems.

2.2 The "science-and-technology backyard" pilot experiment
The Science and Technology Backyard (STB) integrate academic research with field practices so that knowledge from agricultural R&D can be redeveloped using rural smallholders' farming experiences. The STB was developed to serve different crops – ranging from staple crops (wheat, maize, and rice) to cash crops (apple, banana, tea, and mandarin) – working with different stakeholders (including researchers, local governments,

non-government organizations, and private companies) in rural villages. In our study, we specifically focus on STBs developed to serve local smallholders in *wheat-and-maize* production in the NCP [4]. Thirteen STBs have served villages across four townships in Quzhou County of Handan Prefecture since 2009. We chose this experimental program because smallholder farming is the most prevalent farming system in the NCP (Huang *et al.*, 2012b), and the NCP region is one of China's most important grain-producing regions (Zhang *et al.*, 2016).

The STB operates in a highly site-specific approach with three core components: (1) farmer field schools, (2) local field demonstrations, and (3) case-to-case counseling. The organization of these activities is demand-driven. To serve smallholders, the local executive team developed four general principles for compliance (Zhang *et al.*, 2016). First, the zero-fee principle requires that all STBs serve smallholders without requesting a service fee. Local extension staff argued that an inclusive service, in which all smallholders had a chance to participate and receive the services, could only be delivered if the zero-fee principle was implemented. Second, the zero-distance principle requires that all STB services be delivered locally within the rural community (in the village or farm). This principle, as argued, is crucial for ensuring that an interactive relationship between STB staff and rural smallholders is achieved. Third, the zero-time difference principle. STB services should be delivered to rural smallholders in a timely manner, with no delay in important information and field practices. Finally, the inclusive (or zero-criteria) principle indicates that STB services are nonexclusive. All stakeholders are eligible to participate and interact with the local STB staff, and all STB activities are open to local community members. More details regarding the STB activities can be found in Zhang *et al.* (2016).

3. Research design
3.1 Sampling and data collection
We conducted a large-scale household survey from February to March 2018 in four counties in Handan prefecture (including the experiment county [Quzhou] and three neighboring counties) to examine the effect of the STB program on smallholder grain production and soil nutrient management. Handan Prefecture is a typical smallholder farming region in the NCP (Tan *et al.*, 2006), with maize and wheat rotation being the most common staple crops. With 35,265 yuan (about 5,250 USD) per capita GDP in 2016, about 12.5% of the total GDP in Handan Prefecture was from the agricultural sector, which was significantly higher than the national average (8.56%, NBS, 2017). The three selected neighboring counties have identical climatic conditions and share the same type of soil (cinnamon soil) [5]. Therefore, we were less concerned about the inconsistencies in outcomes caused by climatic or soil differences.

The sampling was conducted in two steps. First, within the experimental county, 13 villages across four townships had received the STB program since 2009. We further sampled 15 villages that had never received STB services to match these 13 villages [6]. Thus, 28 villages were sampled from the experimental county. Second, we included three neighboring counties that had never received any STB services as the comparison villages to increase the statistical power. We sampled villages within these neighboring counties according to the following criteria: First, the majority of the households within the villages are grain (wheat and maize) farmers (with more than 70% of smallholders being grain producers). This restriction makes STB treatments relevant to local agricultural production conditions. Second, the villages have not received any related training programs or support over the previous five years. This guarantees that our study is not contaminated by other similar agricultural extension programs. Involving these three counties provides us with additional power to test whether there is any statistically significant impact of STB services on rural smallholders' fertilizer use and grain yield. Using these sampling criteria, we sampled 135

rural villages (across 28 townships) for our household survey. Within each sampled village, we randomly selected 16 households to participate in field interviews.

The survey was conducted through face-to-face interviews. Enumerators conducted interviews with household members who were primarily responsible for farming decisions. If more than one household member was in charge of farming activities, the head of the household was the first choice for the interview. This protocol enabled us to consistently collect information within households and guaranteed accurate agricultural input and output information. The household surveys were divided into three groups. In the first block, detailed household demographic information (e.g. the household head's age, education, farming experience, off-farming employment, family size, and family wealth measured by durable goods) was collected. In the second block, we collected detailed household agricultural outputs and input data, including wheat and maize yields, contracted farmland, labor, and machinery inputs. Additionally, information on fertilizer use for maize and wheat production was collected. In the third block, we collected data on village characteristics (including distance to the local township and county seat, village population and farm size, irrigation facilities, and other related agricultural production infrastructure). Table 1 presents descriptive statistics for these variables [7]. These covariates have been frequently used in studies on smallholders' farming practices and agricultural production.

3.2 Analytical approach
3.2.1 Multivariate regression analysis. Given that STB services were provided at the village level, to examine the effect of receiving STB services on smallholders' outcomes, we ran the following multivariate regression analysis (1) as a benchmark estimation:

$$Y_{ij} = \alpha_0 + \alpha_1 T_j + \alpha_2 V_j' + \varepsilon_{ij} \tag{1}$$

In Equation (1), Y_{ij} represents the smallholders' outcomes of interest (including smallholders' yields and nutrient use efficiencies, as presented in Table 2). T_j is a dummy variable indicating whether village j has received STB services, and the coefficient α_1 captures the estimated effect of STB services on smallholder outcomes (Y_{ij}). We also controlled for the village-level observed covariates (V_j'), where ε_{ij} is the robust clustered standard error at the village level. To improve the efficiency of our estimation, we add smallholders' personal and family characteristics (Table 1) to specification (2):

$$Y_{ij} = \beta_0 + \beta_1 T_j + \beta_2 X_{ij}' + \beta_3 V_j' + \varepsilon_{ij} \tag{2}$$

In Equation (2), coefficient β_1 captures the effect of STB services on smallholders' outcomes (Y_{ij}). The vector of X_{ij}' represents the observed smallholders' personal and family characteristics that were not affected by STB services. Adding these control variables could significantly increase estimation efficiency.

Multivariate regression analysis can be informative; however, it does not guarantee an unbiased estimation of the effect of STB services if the assignment of STB villages is not random (i.e. $cov(T_j, \varepsilon_{ij}) \neq 0$, Imbens, 2004). The fundamental challenge in Equations (1) and (2) is whether the selection of STB villages is independent of some previously observed and unobserved village characteristics, which might be correlated with smallholders' outcomes (Imbens, 2004; Rosenbaum, 2010). In other words, when the STB villages (as the treatment group) were not comparable to the non-STB villages (as the control group, Rosenbaum and Rubin, 1983; Heckman *et al.*, 1999), our multivariate regression estimation would be biased due to an invalid counterfactual.

	# Of obs.[c] (1)	Mean (2)	St.dev (3)	minute (4)	Max (5)
Treatment variable					
1. Is a sci-tech backyard village, 1 = yes	135	0.10	0.30	0	1
Household level control variables					
2. Household head's age, in years	1,955	57.53	10.32	26	87
3. Household head's gender, 1 = male	1,955	0.94	0.23	0	1
4. Household head's education, in years	1,955	6.98	3.59	0	16
5. Household head is a village cadre, 1 = yes	1,955	0.06	0.24	0	1
6. Household head is a CCP party member, 1 = yes	1,955	0.14	0.35	0	1
7. Household head is farming, 1 = yes	1,955	0.84	0.37	0	1
8. Household head's risk preference[a]	1,955	4.34	3.20	0	10
9. Household head's internal locus of control[b]	1,955	4.84	0.76	1	6
10. Household head's external locus of control[b]	1,955	2.83	0.98	1	6
11. Family size	1,955	4.69	2.23	1	17
12. Household durable goods	1,955	1.67	0.77	0	3.20
13. Household's total farmland, in hectares	1,955	0.50	0.73	0.2	20
14. Household's farmland pieces	1,955	3.56	2.21	1	15
15. # of household members with off-farm employment	1,955	1.19	1.14	0	7
16. Household received a subsidy, 1 = yes	1,955	0.87	0.34	0	1
Village-level control variables					
17. Village population in 2017	135	1385.19	840.82	300	6,000
18. % of agricultural labor in 2017	135	0.95	0.14	0.18	1
19. Per capita farmland in village, in hectares	135	0.10	0.04	0.03	0.25
20. Number of irrigation wells	135	19.55	14.70	0	65
21. % of migration	135	27.99	18.07	0	86.80
22. Distance to the township seat (km)	135	3.82	2.47	1	12.5
23. Distance to the county seat (km)	135	12.68	7.37	1	45.00

Note(s): [a]We measured household head's general risk preference with a scale from 0 to 10, where 0 stands absolutely risk averse, and 10 stands absolute risk prefer; [b]We controlled household head's personality trait (the internal and external locus of control), which has been frequently examined in technology adoption literature (Ali *et al.*, 2019); [c]In total we surveyed 2,119 rural smallholders. There were 135 smallholders who did not plant either wheat or maize in 2017, while 1921 rural smallholders planted both wheat and maize in 2017. Thus, we have 1,955 smallholders' that planted wheat in 2017, and 1,950 smallholders that planted maize in 2017. Here we report the descriptive statistics of the sample of 1,955 smallholders' that planted wheat

Source(s): Authors' survey in 2018

Table 1.
Description of the control variables

3.2.2 Coarsened exact matching. The cause of an invalid counterfactual may be for two reasons. First, if the analytical sample contains smallholders from both STB and non-STB villages that differ significantly in their background characteristics, the linearity assumption in multivariate regression might produce a biased estimate by extrapolating away from the common support region (King and Zeng, 2006). We used coarsened exact matching (CEM) to create a sample of non-STB villages that share similar observed characteristics with STB villages as the counterfactual to reduce the potential bias (Iacus *et al.*, 2012; Blackwell *et al.*, 2009). We specifically used CEM for two reasons. First, the STB services were delivered at the village level that most smallholders within the village had either directly or indirectly received STB services. A clustered design of the STB program indicates matching should be conducted at the village level instead of among households. With a limited number of villages received STB services, hence, the CEM can maximum reserve the treated samples and match at the village level. Second, the CEM is a monotonic imbalance bounding (MIB) matching method. It requires no assumptions about the data generation process, and the level (covariates) of matching is chosen by the user based on specific, intuitive substantive

Outcome variables	# Of obs.[c] (1)	Mean (2)	st.d (3)	minute (4)	Max (5)
Household grain production outcomes					
1. Wheat *yield* in 2017, kg^{-1} ha	1,955	7,161	937	1,500	10,500
2. Maize *yield* in 2017, kg^{-1} ha	1,950	8,036	1,379	840	14,000
Nutrient (and fertilizer) use efficiency for wheat production[a,b]					
3. Basal nitrate [*N*] applied, kg^{-1} ha	1,054	115.79	32.48	6.91	540
4. Top-dressing nitrate [*N*] applied, kg^{-1} ha	1,054	190.28	119.19	15.87	540
5. Nitrogen use efficiency [*NUE*], kg^{-1} kg	1,054	27.94	13.55	3.55	88.05
6. Basal phosphorous [P] applied, kg^{-1} ha	1,054	110.13	25.97	0	187.88
7. Top-dressing phosphorous [P] applied, kg^{-1} ha	1,054	37.91	52.72	0	168.75
8. Phosphorous use efficiency [*PUE*], kg^{-1} kg	1,054	52.71	18.42	13.33	133.33
9. Basal potassium [K] applied, kg^{-1} ha	1,054	109.17	26.70	0	187.88
10. Top-dressing potassium [K] applied, kg^{-1} ha	1,054	39.04	58.01	0	577.50
11. Potassium use efficiency [*KUE*], kg^{-1} kg	1,054	53.24	19.74	10.87	191.39
Nutrient (and fertilizer) use efficiency for maize production[a,b]					
12. Basal nitrate [*N*] applied, kg^{-1} ha	1,053	110.70	32.29	2.76	405
13. Top-dressing nitrate [*N*] applied, kg^{-1} ha	1,053	89.49	127.63	17.25	574
14. Nitrate use efficiency [*NUE*], kg^{-1} kg	1,053	55.04	27.95	2.51	171.67
15. Basal phosphorus [P] applied, kg^{-1} ha	1,053	104.37	23.94	0	189
16. Top-dressing phosphorus [P] applied, kg^{-1} ha	1,053	16.70	39.37	0	192
17. Phosphorus use efficiency [*PUE*], kg^{-1} kg	1,053	69.18	20.66	7.47	138
18. Basal potassium [K] applied, kg^{-1} ha	1,053	103.84	24.35	0	248
19. Top-dressing potassium [K] applied, kg^{-1} ha	1,053	16.65	39.47	0	270
20. Potassium use efficiency [*KUE*], kg^{-1} kg	1,053	69.67	21.32	7.47	171.67

Note(s): [a]The fertilizers were generally applied twice during the crop-growth period: the basal fertilizer was applied either before the seeding (for wheat) or during the seeding (for maize), and the top-dressing fertilizer was applied during the plants' growth before the grain formation; [b]The nutrient use efficiencies (incl. NUE, PUE and KUE) were calculated based on the total fertilizer applied and the final harvest (same measures as in Zhang *et al.* (2016)); [c]We randomly selected 50% of the sample to collect the detailed fertilizer use and nutrient input data. In total we have 1,038 rural smallholder with detailed data on both wheat and maize nutrient use, 16 smallholders with nutrient data for wheat production only, and 15 smallholders with nutrient data for maize production only

Source(s): Authors' survey in 2018

information with *ex ante* choices. Thus, the imbalance between the matched treated and control groups will not be larger than the *ex ante* user choice (Kumar *et al.*, 2019). Online Appendix 1 presents the covariate balance check before and after CEM implementation. Our estimators are doubly robust under the conditional independent assumption (CIA) and by running regression analyses as in Equation (2) on top of the matched villages, in the sense that the estimators are unbiased if either the matching procedure or the regression specification is correctly specified (Ho *et al.*, 2007; Bang and Robins, 2005).

Second, the use of matching could reduce the bias due to selection of observables, providing no assurance that the assignment of the STB meets the CIA due to unobservables (or hidden-bias, Imbens, 2004; Ichino *et al.*, 2008; Rosenbaum, 2010). Given that the program was implemented *a priori*, it was impossible to test CIA. We used the Rosenbaum bounds analysis to estimate any "hidden bias" caused by unobserved covariates, which may bias our interference. We present the results of the Rosenbaum bounds analysis online, in Appendix 2 with additional discussions.

3.2.3 Robustness check using the (endogenous) switching regression approach. We employ another strand of econometric method – the (endogenous) switching regression approach

([Maddala, 1986](); [Lokshin and Sajaia, 2004](); [Abdulai and Huffman, 2014]())–to examine whether our multivariate regression and CEM estimations suffer from endogeneity issues due to the unobserved sample self-selection problem ([Heckman, 1979]()). We assume that the selection of villages receiving STB services is determined by the following selection [Equation (3)]():

$$T_j^* = \alpha + \gamma' Z_j' + \varepsilon_j, \ T_j^{STB} = 1 \left[T_j^* > 0 \right] \tag{3}$$

where T_j^{STB} is a binary variable indicating if village j received STB services or not; Z_j' is a vector of exogenous village characteristics, and γ' is a vector of parameters to be estimated. The error term ε_j with a mean of zero and variance σ_ε^2 captures the unobserved factors.

Given that smallholders in the sampled villages either received STB services ($T_j^{STB} = 1$) or not ($T_j^{STB} = 0$), we observed that smallholders' outcomes take the following two regimes:

Regime 1 (village received STB services): $\quad Y_{ij}^1 = \alpha_1 + \beta_1 X_{ij}^1 + \mu_{ij}^1 \quad iff \ T_j^{STB} = 1$

Regime 0 (village received no STB services): $Y_{ij}^2 = \alpha_2 + \beta_2 X_{ij}^2 + \mu_{ij}^2 \quad iff \ T_j^{STB} = 0$ (4)

where Y_{ij}^1 and Y_{ij}^2 are the outcomes of smallholders from STB villages and non-STB villages, respectively; X_{ij}^1 and X_{ij}^2 are vectors of smallholders' exogenous characteristics. The three error terms ($\mu_{ij}^1, \mu_{ij}^2, \varepsilon_j$) are assumed to have a tri-variate normal distribution with a mean vector of zero and the following covariance matrix:

$$cov\left(\mu_{ij}^1, \ \mu_{ij}^2, \ \varepsilon_j\right) = \begin{bmatrix} \sigma_{\mu1}^2 & 0 & \sigma_{\mu1\varepsilon} \\ 0 & \sigma_{\mu2}^2 & \sigma_{2\varepsilon} \\ \sigma_{\mu1\varepsilon} & \sigma_{\mu2\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix} \tag{5}$$

where $var(\mu_{ij}^1) = \sigma_1^2$, $var(\mu_{ij}^2) = \sigma_2^2$, $var(\varepsilon_j) = \sigma_\varepsilon^2$, assuming $cov(\mu_{ij}^1, \mu_{ij}^2) = 0$, the correlations $cov(\mu_{ij}^1, \varepsilon_j) = \sigma_{1\varepsilon}$, and $cov(\mu_{ij}^2, \varepsilon_j) = \sigma_{2\varepsilon}$. When there is an unobserved self-selection factor that affects villages receiving STB services (T_j^{STB}) and smallholder outcomes (Y_{ij}'), the correlations of the error terms of the outcomes (μ_{ij}') and the choice equation (ε_j) will take a non-zero value, and the multivariate regression estimates will suffer from sample selection bias ([Lee, 1982]()). Together, [Equations (3), (4), and (5)]() constitute a switching regression model (SRM).

We used the full information maximum likelihood method to estimate the parameters ([Lokshin and Sajiia, 2004]()) to simultaneously estimate choice [Equation (3)]() and outcome [Equation (4)](). The identification of the model requires at least one variable in vector Z_j', which is not included in vector X_{ij}'. Specifically, in [Equation (3)](), the exploratory variables include a vector of variables that might influence the assignment of the villages to receive STB services, and a vector of instrumental variables that is correlated with the (endogenous) treatment variable but uncorrelated with the error term in [Equation (3)](). In our study, we included two instrumental variables, including a binary variable indicating whether a village was a new socialist model village, and found that the average share of smallholders is CCP party members [8]. Once the parameters are estimated, we can identify if there is a sample selection bias due to unobserved factors and the average treatment effect on the treated (ATT) STB services.

4. Empirical results

4.1 Effect of the STB on smallholders' grain productivity

The descriptive results shown in [Table 3]() indicate that smallholders from STB villages have higher yields than those from non-STB villages in both wheat and maize production ([Table 3]()),

	All sampled households[a] (1)	Households from the pilot county[b]			Households from all non-STB villages (5)	Mean differences (6) = (2)–(5)
		STB villages (2)	Non-STB villages (3)	Mean differences[c] (4) = (2)–(3)		
Household wheat production						
# of wheat farmers	*1955*	*194*	*208*	*402*	*1761*	*1955*
# of wheat farmers with NUE data	*1,054*	*115*	*111*	*226*	*939*	*1,054*
1. Yield, kg^{-1} ha	7,161 [937]	7,412 (73)	6,912 (119)	500*** (137)	7,133 (37)	279*** (79)
3. Nitrates use efficiency (NUE), kg^{-1} kg	27.95 [13.61]	31.41 (1.07)	31.53 (1.83)	−0.13 (2.08)	27.52 (0.63)	3.88*** (1.21)
5. Phosphorus use efficiency (PUE), kg^{-1} kg	52.71 [18.42]	56.33 (2.81)	49.97 (1.88)	6.36* (3.32)	52.27 (0.82)	4.06 (2.84)
7. Potassium use efficiency (KUE), kg^{-1} kg	53.24 [19.74]	57.76 (3.06)	49.95 (1.84)	7.82** (3.50)	52.69 (0.86)	5.08 (3.07)
Household maize production						
# of maize farmers	*1950*	*194*	*205*	*399*	*1756*	*1950*
# of maize farmers with NUE data	*1,053*	*116*	*110*	*224*	*937*	*1,053*
9. Yield, kg^{-1} ha	8,036 [1,379]	8,127 (102)	7,617 (113)	510*** (150)	8,026 (47)	101 (109)
11. Nitrates use efficiency (NUE), kg^{-1} kg	55.04 [27.95]	58.35 (3.93)	53.70 (3.17)	4.65 (4.96)	54.63 (1.18)	3.71 (3.97)
13. Phosphorus use efficiency (PUE), kg^{-1} kg	69.18 [20.66]	74.37 (2.13)	66.49 (2.69)	7.88** (3.38)	68.55 (0.88)	5.82** (2.24)
15. Potassium use efficiency (KUE), kg^{-1} kg	69.67 [21.32]	75.90 (2.33)	67.17 (2.71)	8.73** (3.51)	68.92 (0.89)	6.98*** (2.41)

Note(s): [a]In column 1 we report the mean of each outcome variable and its standard deviation in brackets. In columns 2, 3 and 5 we report the mean value of each outcome variable and its estimated village-clustered standard errors; [b]Given that all STB villages were located in one pilot county, we first conduct a descriptive comparison over each outcome within the pilot county between STB villages and non-STB villages. However, given the limited number of sampled villages within the pilot county, the remaining regression analysis will only be conducted with all sampled villages (column 5); [c]Mean differences were calculated by running a series of t-tests, and the standard errors were calculated using a village-clustered robust standard errors for inference, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Authors' survey in 2018

Table 3.
Outcome comparisons between smallholders from STB and non-STB villages

rows 1 and 5). The yield differences in wheat production are substantial (~279 kg per hectare). In the multivariate regression analysis, after controlling for the villages' characteristics (Model 1) and subsequently with additional control of household characteristics (Model 2), we find a robust consistent result. On average, households from STB villages produce about 0.23–0.27 standard deviation (about 250 kg) more wheat per hectare than non-STB villages (Table 4, row 1). The results from the matched-sample regression analysis produce roughly the same results.

However, the results on maize production are inconclusive. The descriptive results show that smallholders from STB villages produce a higher maize yield than those from non-STB villages; the difference is rather small (about 101 kg per hectare) and statistically insignificant. Multivariate regression analysis with Models (1) and (2) produce the same and insignificant results (only about 0.11 standard deviation increase, Table 4, row 4). These results indicate that, at least in 2017, a limited positive impact of STB services could be observed on maize yield.

4.2 Effect of the STB on smallholders' nutrient use efficiency and fertilizer application

Regarding smallholders' soil nutrient use efficiency (in N-P-K), we find inconsistent results. For instance, in wheat production, smallholders from STB villages show a significant improvement in nitrogen use efficiency (approximately 3.88 kg additional wheat producer per kg nitrogen applied, Table 3, row 2); however, no significant positive improvement is observed in phosphorus and potassium use efficiency. In contrast, for maize production, the results are reversed. We find no significant improvement in nitrogen use efficiency but significant improvements in phosphorus and potassium use efficiencies (Table 3, rows 7–8).

The multivariate regression and matching results in Table 5 show that there was a statistically significant increase in nutrient use efficiency across all nutrients (N, P, and K) in

| | Ordinary least square (OLS) | | Coarse exact match with OLS adjustment |
	Model 1 (1)	Model 2 (2)	(3)
Panel A: Households' wheat yield, normalized			
Treatment variable			
1. Is a STB village, 1 = yes	0.27*** (0.09)	0.22** (0.09)	0.23** (0.10)
2. Individual and family characteristics controlled		*Yes*	*Yes*
3. Village characteristics	*Yes*	*Yes*	*Yes*
Mean (kg per hectare)	7,161		7,245
Standard deviations	[937]		[913]
# of clusters	135		65
# of households	1,955		952
Panel B: Households' maize yield, normalized			
Treatment variable			
4. Is a STB village, 1 = yes	0.12 (0.08)	0.09 (0.08)	0.11 (0.10)
5. Individual and family characteristics controlled		*Yes*	*Yes*
6. Village characteristics	*Yes*	*Yes*	*Yes*
Mean (kg per hectare)	8,036		8,124
Standard deviations	[1,379]		[1,353]
# of clusters	135		65
# of households	1,950		950

Note(s): Robust clustered-standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' survey in 2018

Table 4.
Effect of STB on rural smallholders' grain yields, normalized

	Wheat production			Maize production		
	Ordinary least square (OLS)		Coarse exact match with OLS adjustment	Ordinary least square (OLS)		Coarse exact match with OLS adjustment
	Model 1 (1)	Model 2 (2)	(3)	Model 1 (4)	Model 2 (5)	(6)
Panel 1: Nitrogen use efficiency (NUE), kg⁻¹ kg						
Treatment variable						
1. Is a STB village, 1 = yes	3.03** (1.34)	3.28*** (1.32)	2.51* (1.45)	1.97 (4.26)	1.86 (4.33)	2.27 (4.04)
2. Individual and family characteristics controlled	Yes	Yes	Yes	Yes	Yes	Yes
3. Village characteristics		Yes	Yes		Yes	Yes
Mean (kg per kg)		27.95	28.34		55.04	55.92
Standard deviations		[13.61]	[13.48]		[27.95]	[28.90]
# of clusters		135	65		135	65
# of households		1,054	518		1,053	510
Panel 2: Phosphorus use efficiency (PUE), kg⁻¹ kg						
Treatment variable						
4. Is a STB village, 1 = yes	3.84 (2.42)	4.42* (2.33)	6.47** (2.64)	4.92** (2.42)	5.02** (2.34)	4.68** (2.13)
6. Individual and family characteristics controlled	Yes	Yes	Yes	Yes	Yes	Yes
7. Village characteristics		Yes	Yes		Yes	Yes
Mean (kg per kg)		52.71	52.99		69.18	70.43
Standard deviations		[18.42]	[18.96]		[20.66]	[20.81]
# of clusters		135	65		135	65
# of households		1,054	518		1,053	510
Panel 3: Potassium use efficiency (KUE), kg⁻¹ kg						
Treatment variable						
8. Is a STB village, 1 = yes	4.68* (2.54)	5.59** (2.48)	7.59*** (2.84)	5.78** (2.52)	5.91** (2.48)	5.30** (2.49)
10. Individual and family characteristics controlled	Yes	Yes	Yes	Yes	Yes	Yes
11. Village characteristics		Yes	Yes		Yes	Yes
Mean (kg per kg)		53.24	53.57		69.67	71.07
Standard deviations		[19.74]	[20.75]		[21.32]	[21.92]
# of clusters		135	65		135	65
# of households		1,054	518		1,053	510

Note(s): Robust clustered-standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Authors' survey in 2018

Table 5.
Effect of STB on smallholders' nutrient use efficiency, OLS and matching result

wheat production. The regression results indicate consistent results. Specifically, per kilogram nitrogen application yielded an additional 2.5–3.3 kg wheat produced per hectare (Table 5, row 1) than comparison villages; additional wheat per kilogram of phosphorus applied, Panel efficiency (Row 4.42–6.47 kg additional wheat per kilogram of potassium applied, Panel 2, Row 4; and 4.68–7.59 kg additional wheat per kilogram of potassium applied, Panel 3, Row 7). These results indicate that the STB program has indeed improved smallholder nutrient use efficiency in wheat production. In maize production, we find significant increases in P and K use efficiency (Table 5, rows 4 and 7), but no significant increase in N use efficiency.

Comparing the nutrient use efficiency of wheat and maize production and the differences in wheat and maize yields, we notice that there is a large and robust improvement in phosphorus and potassium use efficiencies, whereas the increase in nitrogen use efficiency is rather weak and statistically insignificant. Given that applying fertilizer is a common practice among smallholders, the question arises as to why we find inconsistent results between wheat and maize; and between nitrogen use efficiency (NUE), phosphorous (PUE), and potassium (KUE) use efficiencies.

Interviews with the field STB staff indicate that there were two potential causes for this inconsistency. First, the application of fertilizer is not only about the amount applied, but also about when it is applied. The base fertilizer is crucial for fostering plant germination; however, not intensified. Smallholders often intensively apply base fertilizer but avoid top-dressing fertilization. The naïve belief is that as long as the total amount of fertilizer is applied, nutrients remain in the soil. Although this approach can save a substantial amount of labor input, it results in excessive nutrient loss. In field training, STB staff encourages smallholders to reduce the base fertilizer application (particularly nitrogen) and ensure top-dressing, which is crucial for grain formation (an essential step in improving yields). Thus, we should be able to observe a decrease in base fertilizer use.

Second, the nutrient demands of wheat and maize are essentially different. Unlike wheat production, N is particularly important for maize growth during the jointing stage and grain formation (Cui et al., 2010). STB staff emphasizes the reduction of base fertilizer in both wheat and maize production. However, they recommend a reduction in top-dressing fertilization for wheat production and a slight increase in maize production since more than 95% of smallholders practice top-dressing fertilization for wheat production, and some smallholders might still intensively apply chemical fertilizers. In contrast, in maize production, less than 40% of smallholders were in fact applying top-dressing fertilizers due to the high temperatures in summer and the physical difficulties involved. This leads to a lack of nitrogen for maize formation, which further decreases maize yield.

We further analyzed the amount of nitrogen applied in base fertilization and top-dressing fertilization separately to verify whether this field practice might cause a discrepancy in nitrogen use efficiency and maize yield [9]. Figure 1 shows the basic descriptive comparisons of the base and top-dressing fertilizations between smallholders from STB and non-STB villages. We found a statistically significant reduction in base fertilizer application in both wheat and maize production (Table 6, Panel 1). However, regarding top-dressing fertilization, we found a significant reduction in wheat production (approximately 0.22–0.28 standard deviation; Table 6, Panel 2), but no increase or decrease in maize production. This result indicates that the change in smallholder top-dressing fertilization in maize production is limited.
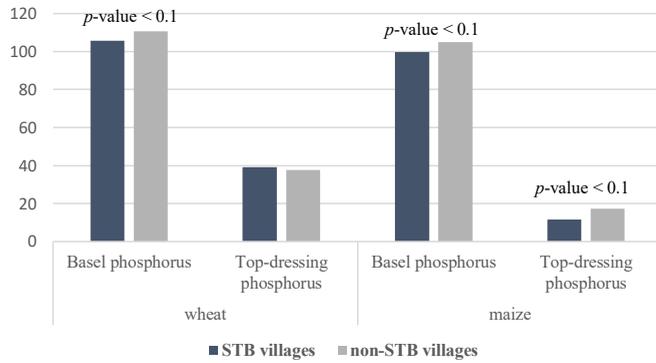
4.3 The (endogenous) switching regression estimations
Tables 7 and 8 present the (endogenous) switching regression estimations for both wheat and maize yields. The selection equations are provided in Column 1 using the full information

Panel A: Nitrogen applications in wheat and maize production
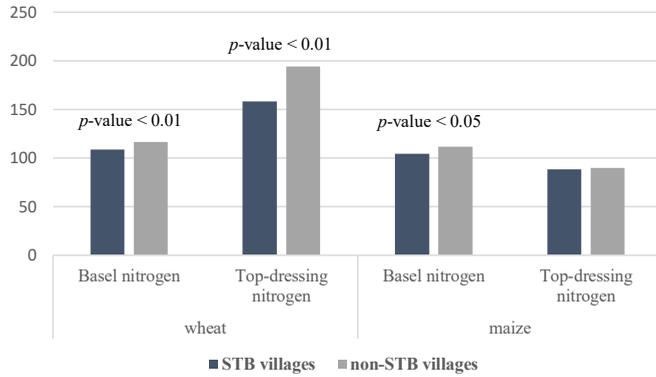
Panel B: Phosphorus applications in wheat and maize production

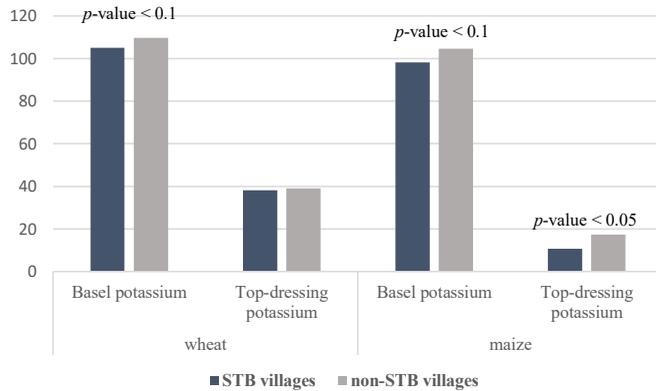*Panel C: Potassium application in wheat and maize production*

Source(s): Authors' survey in 2018

Figure 1.
Comparisons of smallholders' amount of fertilizer application

Outcomes	Wheat production in 2017			Maize production in 2017		
	Ordinary least square (OLS) Mode 1 (1)	Model 2 (2)	Coarse exact match with OLS adjustment (3)	Ordinary least square (OLS) Model 1 (4)	Model 2 (5)	Coarse exact match with OLS adjustment (6)
Panel 1: The amount of nitrogen applied in the base fertilization (kg per hectare)						
Treatment variable						
1. Is a STB village, 1 = yes	−0.29*** (0.08)	−0.29*** (0.09)	−0.25** (0.10)	−0.22** (0.10)	−0.21* (0.11)	−0.36*** (0.11)
2. Individual and family characteristics controlled		*Yes*	*Yes*		*Yes*	*Yes*
3. Village characteristics	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Mean (kg per hectare)	115.79		114.57	110.70		113.03
Standard deviations	[32.48]		[27.59]	[32.29]		[38.30]
# of clusters	135		65	135		65
# of households	1,054		523	1,053		517
Panel 2: The amount of nitrogen applied in the top-dressing fertilization (kg per hectare)						
Treatment variable						
4. Is a STB village, 1 = yes	−0.28*** (0.10)	−0.25** (0.10)	−0.22* (0.12)	0.05 (0.12)	0.06 (0.12)	0.07 (0.13)
5. Individual and family characteristics controlled		*Yes*	*Yes*		*Yes*	*Yes*
6. Village characteristics	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Mean (kg per hectare)	190.28		188.66	89.49		90.53
Standard deviations	[119.19]		[119.89]	[127.63]		[124.97]
# of clusters	135		65	135		65
# of households	1,054		523	1,053		517

Note(s): Robust clustered-standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' survey in 2018

Table 6.
Effect of STB on smallholders' base and top-dressing fertilization

| | | Wheat yield, normalized | |
| | | STB villages | Non-STB villages |
	Selection (1)	$[T_j^{STB} = 1]$ (2)	$[T_j^{STB} = 0]$ (3)
1. Constant	−0.93 (1.36)	−1.65* (0.94)	−1.82*** (0.48)
2. HH's age, in years	−0.00 (0.01)	−0.00 (0.01)	0.01*** (0.00)
3. HH's gender, 1 = male	−0.15 (0.19)	−0.16 (0.46)	0.14 (0.11)
4. HH's education, in years	0.05*** (0.02)	0.00 (0.02)	0.01 (0.01)
5. HH is a village cadre, 1 = yes	−0.14 (0.19)	−0.56 (0.38)	0.14 (0.09)
6. HH is a CCP party member, 1 = yes	−0.12 (0.10)	0.45* (0.26)	0.08 (0.09)
7. HH is farming, 1 = yes	−0.02 (0.14)	0.25 (0.20)	0.07 (0.07)
8. HH's risk prefecture	0.01 (0.01)	0.00 (0.03)	0.00 (0.01)
9. HH's internal locus of control	0.11** (0.05)	0.05 (0.09)	0.09** (0.04)
10. HH's external locus of control	−0.15*** (0.04)	−0.05 (0.06)	−0.03 (0.03)
11. Family size, in persons	0.01 (0.02)	0.03 (0.03)	−0.02 (0.02)
12. Household durable goods	−0.06 (0.06)	0.10 (0.11)	0.13*** (0.04)
13. Household's total farmland, in hectares	−0.35 (0.23)	−0.04 (0.20)	0.02 (0.02)
14. Household's farmland pieces	0.14*** (0.04)	0.06** (0.03)	0.03** (0.01)
15. # of HH with off-farm employment	−0.04 (0.05)	−0.07 (0.07)	−0.01 (0.03)
16. Household has received a subsidy, 1 = yes	0.06 (0.14)	0.20 (0.17)	0.11 (0.08)
17. Village population in 2017	0.00 (0.00)	0.00*** (0.00)	−0.00 (0.00)
18. % of agricultural labor in 2017	−1.36 (1.03)	−0.93** (0.46)	0.26 (0.28)
19. Per capita farmland in village, in hectares	6.34 (4.44)	10.90*** (1.83)	1.79 (1.25)
20. % of migration at village level	−0.00 (0.01)	−0.00 (0.00)	0.00 (0.00)
21. Distance to the township (km)	0.01 (0.07)	0.02 (0.03)	−0.00 (0.02)
22. Distance to the county seat (km)	0.00 (0.02)	−0.01 (0.01)	−0.01 (0.01)
23. Village is a socialist model village, 1 = yes	−6.85*** (0.36)		
24. % of CCP party member in village	−2.49 (1.78)		
25. Sigma 1 ($\sigma_{\mu1}$)		0.88 (0.09)	
26. R1		0.29 (0.19)	
27. rho_1 ($\sigma_{\mu1\varepsilon}$)		*0.28 (0.17)*	
28. Sigma 2 ($\sigma_{\mu2}$)			0.98 (0.03)
29. R2			−0.02 (0.03)
30. rho_2 ($\sigma_{\mu2\varepsilon}$)			*0.17 (0.28)*
31. Log likelihood	−3241.61		
32. Wald test of independent equations $\chi^2(1)$	54.74*** *p*-value = 0.00		

Note(s): Robust clustered-standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' survey in 2018

Table 7.
Endogenous switching regression results for STB villages and non-STB villages on smallholders' wheat yield

maximum likelihood approach, which jointly estimates the selection the outcome equations. In both specifications, the estimated coefficients of the selection equation are slightly different, because we use the full information maximum likelihood approach [10]. In both specifications, the coefficients of the selection equation show that smallholders' education, locus of control, and number of land pieces have a statistically significant value, although the coefficient of education is rather small (Table 7, Column 1). The coefficient of village is a socialist model

| | Selection (1) | Maize yield, normalized | |
		STB villages $[T_j^{STB} = 1]$ (2)	Non-STB villages $[T_j^{STB} = 0]$ (3)
1. Constant	−1.03 (1.34)	−1.79* (0.91)	−0.72* (0.39)
2. HH's age, in years	−0.00 (0.01)	0.01** (0.01)	−0.00 (0.00)
3. HH's gender, 1 = male	−0.17 (0.19)	0.10 (0.33)	0.11 (0.12)
4. HH's education, in years	0.05*** (0.02)	0.00 (0.02)	−0.00 (0.01)
5. HH is a village cadre, 1 = yes	−0.13 (0.19)	−0.41 (0.27)	0.08 (0.11)
6. HH is a CCP party member, 1 = yes	−0.15 (0.10)	0.59** (0.29)	0.09 (0.08)
7. HH is farming, 1 = yes	−0.02 (0.14)	0.41 (0.28)	0.06 (0.07)
8. HH's risk prefecture	0.01 (0.01)	0.01 (0.02)	0.01* (0.01)
9. HH's internal locus of control	0.13** (0.05)	−0.07 (0.09)	0.09** (0.04)
10. HH's external locus of control	−0.15*** (0.04)	−0.06 (0.07)	−0.01 (0.03)
11. Family size, in persons	0.00 (0.02)	−0.03 (0.02)	−0.00 (0.01)
12. Household durable goods	−0.06 (0.06)	0.19** (0.08)	0.12*** (0.04)
13. Household's total farmland, in hectares	−0.37 (0.23)	−0.27* (0.15)	0.02 (0.04)
14. Household's farmland pieces	0.14*** (0.04)	0.08*** (0.03)	−0.02 (0.02)
15. # of HH with off-farm employment	−0.02 (0.05)	0.09* (0.04)	−0.00 (0.03)
16. Household has received a subsidy, 1 = yes	0.03 (0.13)	−0.24 (0.17)	0.06 (0.08)
17. Village population in 2017	0.00 (0.00)	0.00** (0.00)	−0.00 (0.00)
18. % of agricultural labor in 2017	−1.34 (1.02)	0.03 (0.62)	0.21 (0.19)
19. Per capita farmland in village, in hectares	6.72 (4.32)	2.33 (2.45)	−0.63 (1.06)
20. % of migration at village level	−0.00 (0.01)	−0.00 (0.01)	0.00** (0.00)
21. Distance to the township (km)	0.01 (0.06)	0.05* (0.03)	−0.02 (0.02)
22. Distance to the county seat (km)	−0.00 (0.02)	−0.00 (0.02)	−0.00 (0.01)
23. Village is a socialist model village, 1 = yes	−6.59*** (0.40)		
24. % of CCP party member in village	−2.54 (1.76)		
25. Sigma 1 ($\sigma_{\mu 1}$)		0.84 (0.08)	
26. R1		0.18 (0.24)	
27. rho_1 ($\sigma_{\mu 1 \varepsilon}$)		0.18 (0.24)	
28. Sigma 2 ($\sigma_{\mu 2}$)			1.00 (0.02)
29. R2			−0.32* (0.17)
30. rho_2 ($\sigma_{\mu 2 \varepsilon}$)			−0.31 (0.16)
31. Log likelihood	−3250.27		
32. Wald test of independent equations $\chi^2(1)$	60.67*** p-value = 0.00		

Note(s): Robust clustered-standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' survey in 2018

village, which is statistically significant, indicating that if the village is a model village, there is a low probability of receiving STB services. We also noticed a negative coefficient for the percentage of CCP memberships in the village and the selection of receiving STB services; however, the estimated standard error is large, and it is difficult to reject the null hypothesis.

Second, a more important finding is that the estimates presented at the bottom of Tables 7 and 8 indicate no statistically significant endogenous selection effects. The coefficients of rho_1 ($\sigma_{\mu 1 \varepsilon}$) and rho_2 ($\sigma_{\mu 2 \varepsilon}$) were small and not statistically significant, and the estimated

standard errors are rather large (Tables 7 and 8, Columns 2 and 3). Thus, we cannot reject the null hypothesis that no statistically significant correlations exist between the two error terms. This result implies that there was no unobserved factor affected the selection of villages receiving STB services and affected smallholder wheat and maize yields simultaneously. We also ran the same analyses with smallholder nutrient use efficiencies with N-P-K, smallholder basal fertilization, and top-dressing fertilization. The switching regression results were consistent, with no statistical significance. Thus, the results of either the multivariate regression or CEM estimations should be consistent and robust. This result further echoes the results of the multivariate regression and CEM results. We find limited changes in the estimations using these two methods.

5. Conclusion and discussion

In this paper, we studied a novel agricultural extension model – the "*science and technology backyard (STB)*" – in promoting sustainable farming among rural smallholders in the NCP. Taking a large-scale smallholder survey in early 2018, we used both the multivariate regression, CEM, and the (endogenous) switching regression approaches to examine the long-term effect of STB services on farmers' grain production and soil nutrient use efficiencies. We found that the STB program increased smallholders' grain yields, particularly in wheat production, and reduced smallholders' fertilizer use, particularly basal fertilizer use, subsequently improving smallholders' overall nutrient use efficiency. This result suggests that the STB approach can contribute to a significant reduction in agricultural pollution due to the use of chemical fertilizers.

Considering these quantitative findings, to what extent are the findings of our study comparable to similar international studies? Does the STB program have a substantial effect relative to other programs in other developing countries? To answer these questions, Table 9 presents a summary of similar studies conducted in both China and other developing countries. First, we compared our results to those of Zhang *et al.* (2016). Both studies showed rather consistent results; however, given the focus on applying rigorous impact assessment methods in our research, the scale of our study was much smaller than that of Zhang *et al.* (2016). Considering the differences in research methods and data generation process, it seems that Zhang *et al.* (2016) overestimated the magnitude of the effect of the STB program. Second, most recent studies in this field literature, a substantial number (seven out of 11) of the studies examine the effect of farmer field schools on integrated pesticide management. Most of these studies found significant improvements in farming knowledge (Godtland *et al.*, 2004; Guo *et al.*, 2015; Van Campenhout, 2017); however, with the exception of Davis *et al.* (2012) and Kondylis *et al.* (2017), most of these studies did not provide concrete evidence on smallholders' yield increase or improvement of nutrient use efficiencies.

The STB program shows that technology adoption is important, but that an effective extension requires strategies to identify smallholder's needs, to integrate technologies in the local context, and communicate effectively with local smallholders. However, our study provides no cost-effectiveness analysis of the STB program and its effects beyond grain production and soil nutrient use efficiency. This is partially because the current program collaborates closely with different stakeholders (including public universities, local governments, private companies, and individual donors). A cost-effectiveness analysis will be a crucial next step in examining to what extent the STB model could be further expanded in the long run and to other parts of China.

Finally, a number of limitations should be taken into account. First, although we argue that our sample is representative for smallholder agriculture in the NCP as a whole, care should be taken in extending our findings and conclusions to that larger region without carrying more rigorous evaluations for those other parts of the region. Second, the matching methods that we

Country (1)	Research methods[a] (2)	Treatment of the program[b] (3)	Core outcome variables[c] (4)	Effect of the program (6)	References (7)
China	Descriptive comparisons	STB program	Maize and wheat yield, and nitrate use efficiency (NUE)	– About 500 and 600 kg per ha increase in wheat and maize yield, respectively – NUE increased significantly for both wheat and maize production	Zhang et al. (2016)
China	RCT	FFS with sustainable and low-carbon farm management technologies	Farming knowledge acquisition among rice farmers	– About 7.6% increase in knowledge, with a heterogeneous treatment effect – No results about rice yield, and carbon emissions related to rice production	Guo et al. (2015)
Indonesia	DID	FFS + IPM	Rice yields Pesticide use	– No significant impact observed, either in increasing yield or decreasing insecticides	Feder et al. (2004)
Vietnam	DID	FFS + IPM	Knowledge on IPM, pesticide use and rice yield	– About 56.6% better score on knowledge gain; no significant increase on rice yield	Rejesus et al. (2012)
Thailand	DID	FFS + IPM (over three-year period)	Chemical pesticide reduction, and rice productivity	– Significant reduction of the pesticide application – No effect on rice yield increase	Praneetvatakul and Waibel (2006)
Sri Lanka	RCT	FFS + IPM (over five-year period)	Rice production	– Significant reduction of insecticide application – More likely practicing soil fertility management	Tripp et al. (2005)
Peru	PSM	FFS + IPM	Knowledge gain and potato productivity	– About 14% points increase of farming knowledge – No direct estimation about potato yield	Godtland et al. (2004)
East Africa (incl. Kenya, Tanzania and Uganda)	DID, PSM and covariate matching	FFS + IPPM	Crop productivity Livestock productivity Agricultural income	– Crop productivity increased by 80% in Kenya, and 23% in Tanzania – Livestock production increased 31% in Kenya, and 26% in Uganda – Agricultural income increased by 104% in Tanzania, but much less in Kenya and Uganda	Davis et al. (2012)

(continued)

Table 9.

Country (1)	Research methods[a] (2)	Treatment of the program[b] (3)	Core outcome variables[c] (4)	Effect of the program (6)	References (7)
Uganda	RDD	Extension services and NGO-supported model farmer and community promotion	Advanced maize seeds (HYV) adoption, and food sufficiency	– Minimum impact on adaptation of HYV seeds – About 5.4% points increase of food sufficiency	Pan *et al.* (2018)
Uganda	DID + FE	Agricultural extension with ICT and SMS	Crop structure, and maize productivity	– It has changed crop choices, more commercially oriented crops – However, no increase in maize productivity	Van Campenhout (2017)
Mozambique	RCT	AE through contact farmers (CFs), SLM	Technology adoption, and maize yield (revenue per hectare)	– About 19.6% increase of technology adoption among CFs – Increase contact farmers' maize yield about 0.13–0.24 standard deviation – No further effects for other farmers	Kondylis *et al.* (2017)

Note(s): [a]Abbreviations used in Column 2: DID: Difference-in-Difference estimation; FE: Fixed Effect estimation; PSM: Propensity Score matching; RCT: Randomized Controlled Trail; RDD: Regression Discontinuity Design; [b]Abbreviations used in Column 3: AE: Agricultural Extension; FFS: Famer Field School; IPM: Integrated Pesticide Management; IPPM: Integrated Pest and Production Management; ICT: Information and Communication Technologies; SMS: Short Messages; SLM: Sustainable Land Management; T&V: Training and Visiting model of agricultural extension; [c]Abbreviations used in Column 4: NUE: Nitrate Use Efficiency

applied might effectively reduce the omitted variable bias, they provide no guarantee that other unobserved covariates might not bias our estimation. Sensitivity analysis with Rosenbaum bounds analysis indicated that our results are robust to hidden bias. Moreover, the use of (endogenous) switching regression estimation provides us additional confidence in the robustness of our main findings. Yet, additional more rigorous evaluations based on large-scale randomized controlled experiments are desirable for a more effective empirical evaluation.

Notes

1. Statistics from the Food and Agricultural Organization (FAO) shows that on average Chinese farmers are using more than 300 kg chemical fertilizer per hectare, which is significantly higher than the recommended 225 kg per hectare (Cui *et al.*, 2008), and it is almost three times higher than the OECD members' average amount of fertilizer use (137 kg per hectare, FAO, 2017).

2. This was partially due to the decentralization and privatization trends in public goods provision during 1990s. See Swanson and Samy (2002) for detailed studies about decentralization and privatization of agricultural extension.

3. As a rescue plan and to avoid crop failure due to unforeseen bad weathers (such as flooding, strong winds, and extreme cold), farmers often apply more chemical fertilizers to increase the plant resilience.

4. In Zhang *et al.* (2016), the STB village only includes villages that have STB offices. However, in the field, STB staff serve not only these villages but also other neighboring villages. After consulting with local STB staff, we included all STB villages (including villages that have received STB services without an office) in our study area.

5. To examine the representativeness of the sampled households to the rest of the North China Plain, we compared our sampled smallholders' wheat and maize yield, and farm size distributions with some previous studies in Henan and Shandong provinces (Wang *et al.*, 2020). Our samples have a close distribution with other smallholders in the NCP. Detailed comparisons are available upon the reader's requests.

6. We selected 1–2 neighboring villages per STB village according to the population, farm size and its cropping structures to match with the existing STB villages; all matched villages had never received STB services.

7. In the online Appendix Table A1, we show the comparisons between the STB villages and the non-STB villages over these predetermined control covariates (column 1–3, Table A1).

8. If the village is a socialist model village (as a local government special model village), there is less chance of having a STB program because there will be too much political attention. However, the assignment of the model village has no relationship with smallholder's farming and their agricultural production. The percentage of CCP members indicates the political condition of village governance; higher CCP members often have a high level of turnover at village elections, thus, less probability to receive a STB service.

9. We present the descriptive comparisons between STB villages and non-STB villages regarding the nutrient applications in Figure 1. Panels A, B and C are the comparisons of nitrogen, phosphorous and potassium applications between STB villages and non-STB villages respectively.

10. The full information maximum likelihood (FIML) method estimates the selection equation and smallholder (wheat and maize) yield equation simultaneously to have consistent estimates (Lokshin and Sajaia, 2004).

References

Abdulai, A. and Huffman, W. (2014), "The adoption and impact of soil and water conservation technology: an endogenous switching regression application", *Land Economics*, Vol. 90 No. 1, pp. 26-43.

Ali, D.A., Bowen, D. and Deininger, K. (2019), "Personality traits, technology adoption, and technical efficiency: evidence from smallholder rice farms in Ghana", *Journal of Development Studies*, Vol. 56 No. 519, pp. 1-19, doi: 10.1080/00220388.2019.1666978.

Alston, J.M., Marra, M.C., Pardey, P.G. and Wyatt, T.J. (2000), "Research returns redux: a meta-analysis of the returns to agricultural R&D", *Australian Journal of Agricultural and Resource Economics*, Vol. 44 No. 2, pp. 185-215.

Bang, H. and Robins, J.M. (2005), "Doubly robust estimation in missing data and causal inference models", *Biometrics*, Vol. 61 No. 4, pp. 962-973.

Blackwell, M., Iacus, S., King, G. and Porro, G. (2009), "CEM: coarsened exact matching in Stata", *The Stata Journal*, Vol. 9 No. 4, pp. 524-546.

Carvalho, F. (2006), "Agriculture, pesticides, food security and food safety", *Environmental Science and Policy*, Vol. 9, pp. 685-692.

Chen, X., Zeng, D., Xu, Y. and Fan, X. (2018), "Perception, risk attitude and organic fertilizer investment: evidence from rice and banana farmers in Guangxi, China", *Sustainability*, Vol. 10, p. 3715.

Cui, Z., Chen, X., Miao, Y., Zhang, F., Sun, Q., Schroder, J., Zhang, H., Li, J., Shi, L., Xu, J., Ye, Y., Liu, C., Yang, Z., Zhang, Q., Huang, S. and Bao, D. (2008), "On-farm evaluation of the improved soil Nmin-based nitrogen management for summer maize in North China Plain", *The Agronomy Journal*, Vol. 100 No. 3, pp. 517-525.

Cui, Z., Chen, X. and Zhang, F. (2010), "Current nitrogen management status and measures to improve the intensive wheat-maize system in China", *AMBIO*, Vol. 39, pp. 376-384.

Davis, K., Nkonya, E., Kato, E., Mekonnen, D., Odendo, M., Miiro, R. and Nkuba, J. (2012), "Impact of farmer field schools on agricultural productivity and poverty in East Africa", *World Development*, Vol. 40 No. 2, pp. 402-413.

Duflo, E., Kremer, M. and Robinson, J. (2008), "How high are rates of return to fertilizer? Evidence from field experiments in Kenya", *American Economic Review: Papers and Proceedings*, Vol. 98 No. 2, pp. 482-488.

Fan, M., Shen, J., Yuan, L., Jiang, R., Chen, X., Davies, W.J. and Zhang, F. (2012), "Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China", *Journal of Experimental Botany*, Vol. 63 No. 1, pp. 13-24.

Feder, G., Murgai, R. and Quizon, J.B. (2004), "The acquisition and diffusion of knowledge: the case of pest management training in farmer field schools, Indonesia", *Journal of Agricultural Economics*, Vol. 55 No. 2, pp. 221-243.

Food and Agriculture Organization [FAO] (2017), "FAOSTAT: FAO statistical databases (Rome, Italy)", available at: http://www.fao.org/faostat/en/#data/QC.

Feder, G., Just, R.E. and Zilberman, D. (1985), "Adoption of agricultural innovations in developing countries: a survey", *Economic Development and Cultural Change*, Vol. 33, pp. 255-298.

Garfield, E., Guadagni, M. and Moreau, D. (1996), "Colombia: decentralization of agricultural extension services", *Extension Workshop, Alternative Mechanisms for Funding and Delivering Extension*, World Bank, Washington, District of Columbia.

Ghose, B. (2014), "Food security and food self-sufficiency in China: from past to 2050", *Food and Energy Security*, Vol. 3 No. 2, pp. 86-95.

Godtland, E.M., Sadoulet, E., De Janvry, A., Murgai, R. and Ortiz, O. (2004), "The impact of farmer field schools on knowledge and productivity: a study of potato farmers in the Peruvian Andes", *Economic Development and Cultural Change*, Vol. 53 No. 1, pp. 63-92.

Guo, M., Jia, X., Huang, J., Kumar, K.B. and Burger, N. (2015), "Farmer field school and farmer knowledge acquisition in rice production: experimental evaluation in China", *Agriculture, Ecosystems and Environment*, Vol. 209, pp. 100-107.

Heckman, J. (1979), "Sample selection bias as a specification error", *Econometrica*, Vol. 47 No. 1, pp. 153-161.

Heckman, J.J., LaLonde, R.J. and Smith, J.A. (1999), "The economics and econometrics of active labor market program", *Handbook of Labor Economics*, Vol. 3, pp. 1986-2097.

Ho, D.E., Imai, K., King, G. and Stuart, E.A. (2007), "Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference", *Political Analysis*, Vol. 15 No. 3, pp. 199-236.

Hu, R., Huang, J. and Li, L. (2004), "Zhong Guo Nong Ji Tui Guang: Xian Zhuang, Wen Ti Ji Jie Jue Dui Ce", *Guan Li Shi Jie*, Vol. 5, pp. 50-57, [in Chinese].

Huang, J., Xiang, C., Jia, X. and Hu, R. (2012a), "Impacts of training on farmers' nitrogen use in maize production in Shandong, China", *Journal of Soil and Water Conservation*, Vol. 67, pp. 321-327.

Huang, J., Wang, X. and Qui, H. (2012b), *Small-Scale Farmers in China in the Face of Modernization and Globalization*, IIED/HIVOS, London and The Hague.

Huang, J. and Yang, G. (2017), "Understanding recent challenges and new food policy in China", *Global Food Security*, Vol. 12, pp. 119-126.

Iacus, S.M., King, G. and Porro, G. (2012), "Causal inference without balance checking: coarsened exact matching", *Political Analysis*, Vol. 20, pp. 1-24.

Ichino, A., Mealli, F. and Nannicini, T. (2008), "From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity?", *Journal of Applied Econometrics*, Vol. 23 No. 3, pp. 305-327.

Imbens, G.W. (2004), "Nonparametric estimation of average treatment effects under exogeneity: a review", *Review of Economics and Statistics*, Vol. 86 No. 1, pp. 4-29.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F. and Mekuria, M. (2013), "Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania", *Technological Forecasting and Social Change*, Vol. 80 No. 3, pp. 525-540.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P. and Erenstein, O. (2015), "Understanding the adoption of a portfolio of sustainable intensification practices in eastern and Southern Africa", *Land Use Policy*, Vol. 42, pp. 400-411.

King, G. and Zeng, L. (2006), "The dangers of extreme counterfactuals", *Political Analysis*, Vol. 14 No. 2, pp. 131-159.

Kondylis, F., Mueller, V. and Zhu, J. (2017), "Seeing is believing? Evidence from an extension network experiment", *Journal of Development Economics*, Vol. 125, pp. 1-20.

Kumar, A., Verma, S., Prasad, A., Kishore, A. and Saroj, S. (2019), *The Million Farmers School: An Evaluation of its Impact on Farmers' Agricultural Knowledge in Uttar Pradesh, India*, IFPRI Discussion Paper 01888, South Asia Regional Office, New Delhi.

Lee, L.F. (1982), "Some approaches to the correction of selectivity bias", *Review of Economic Studies*, Vol. 49 No. 3, pp. 355-372.

Lokshin, M. and Sajaia, Z. (2004), "Maximum likelihood estimation of endogenous switching regression models", *The Stata Journal*, Vol. 4 No. 3, pp. 282-289.

Maddala, G.S. (1986), "Disequilibrium, self-selection, and switching models", *Handbook of Econometrics*, Vol. 3, pp. 1633-1688.

Ministry of Agriculture [MoA] (2016), "China's rice bowl must be held in Chinese hands: brief of CCP's grain production development strategy since 2012", [in Chinese], available at: http://www.moa.gov.cn/ztzl/xy19d/fzcj/201709/t20170928_5830312.htm.

National Bureau of Statistics [NBS] (2012), *China Statistic Yearbook 2012*, China Statistical Press, Beijing.

National Bureau of Statistics [NBS] (2017), *China Statistic Yearbook: Hebei Province 2017*, China Statistical Press, Beijing.

Norse, D. and Ju, X. (2015), "Environmental costs of China's food security", *Agriculture, Ecosystem and Environment*, Vol. 209, pp. 5-14.

Pan, Y., Smith, S.C. and Sulaiman, M. (2018), "Agricultural extension and technology adoption for food security: evidence from Uganda", *American Journal of Agricultural Economics*, Vol. 100 No. 4, pp. 1012-1031.

Pimentel, D. (1996), "Green revolution agriculture and chemical hazards", *The Science of the Total Environment*, Vol. 188 No. S1, pp. 86-98.

Pingali, P. (2007), "Agricultural mechanization: adoption patterns and economic impact", in Evenson, R.E. and Pingali, R. (Eds), *Handbook of Agricultural Economics*, Vol. 3, pp. 2779-2805.

Praneetvatakul, S. and Waibel, H. (2006), "Impact assessment of farmer field school: using a multi-period panel data model", *International Association of Agricultural Economist Conference*.

Pretty, J., Toulmin, C. and Williams, S. (2011), "Sustainable intensification in African agriculture", *International Journal of Agricultural Sustainability*, Vol. 9, pp. 5-24.

Qiao, F., Zhang, L. and Hu, R. (1999), "Nong Ye Ji Shu Tui Guang Ren Yuan De Tui Guang Xing Wei Fen Xi", *Nong Ye Ji Shu Jing Ji*, Vol. 3, pp. 12-15, [in Chinese].

Qu, F., Kuyvenhoven, A., Shi, X. and Heerink, N. (2011), "Sustainable natural resource use in rural China: recent trends and policies", *China Economic Review*, Vol. 22 No. 4, pp. 444-460.

Rapsomanikis, G. (2015), *The Economic Lives of Smallholder Farmers: An Analysis Based on Household Data from Nine Countries*, Food and Agriculture Organization of the United Nation, Rome.

Rejesus, R.M., Mutuc, M.E.M., Yasar, M., Lapitan, A.V., Palis, F.G. and Chi, T.T.N. (2012), "Sending Vietnamese rice farmers back to school: further evidence on the impacts of farmer field schools", *Canadian Journal of Agricultural Economics/Revue Canadienne d'Agroeconomie*, Vol. 60 No. 3, pp. 407-426.

Rivera, W. (1997), "Agricultural extension into the next decade", *European Journal of Agricultural Education and Extension*, Vol. 4 No. 1, pp. 29-38.

Robinson, L.W., Ericksen, P.J., Chesterman, S. and Worden, J.S. (2015), "Sustainable intensification in drylands: what resilience and vulnerability can tell us", *Agricultural Systems*, Vol. 135, pp. 133-140.

Rosenbaum, P.R. (2010), *Design of Observational Studies*, Springer, New York.

Rosenbaum, P.R. and Rubin, D.B. (1983), "The central role of the propensity score in observational studies for causal effects", *Biometrika*, Vol. 70 No. 1, pp. 41-55.

Schut, M., Asten, P., Okafor, C., Hicintuka, C., Mapatano, S., Nabahungu, N., Kagabo, D., Muchunguzi, P., Njukwe, E., Dontsop-Nguezet, P., Sartas, M. and Vanlauwe, B. (2016), "Sustainable intensification of agricultural systems in the Central African highlands: the need for institutional innovation", *Agricultural Systems*, Vol. 145, pp. 165-176.

Sulaiman, R. and Sadamate, V. (2000), *Privatizing Agricultural Extension in India*, Policy paper 10, National Centre for Agricultural Economics and Policy Research, New Delhi.

Swanson, B. (2006a), "Extension strategies for poverty alleviation: lessons from China and India", *Journal of Agricultural Education and Extension*, Vol. 12 No. 4, pp. 285-299.

Swanson, B. (2006b), "Seminal article series: the changing role of agricultural extension in a global economy", *Urbana*, Vol. 51, 61801.

Swanson, B., Nie, C. and Feng, Y. (2003), "Trends and developments within the Chinese agro-technical extension system", *Journal of the Association of International Agricultural and Extension Education*, Vol. 10 No. 2, pp. 17-24.

Swanson, B. and Samy, M. (2002), "Developing an extension partnership among public, private, and nongovernmental organizations", *Journal of International Agricultural and Extension Education*, Vol. 9 No. 1, pp. 5-10.

Takahashi, K. and Barrett, C.B. (2014), "The system of rice intensification and its impacts on household income and child schooling: evidence from rural Indonesia", *American Journal of Agricultural Economics*, Vol. 96 No. 1, pp. 269-289.

Tan, S., Heerink, N. and Qu, F. (2006), "Land fragmentation and its driving forces in China", *Land Use Policy*, Vol. 23, pp. 272-285.

Tripp, R., Wijeratne, M. and Piyadasa, V.H. (2005), "What should we expect from farmer field schools? A Sri Lanka case study", *World Development*, Vol. 33 No. 10, pp. 1705-1720.

Udry, C. (1990), "Credit markets in Northern Nigeria: credit as insurance in a rural economy", *World Bank Economic Review*, Vol. 4, pp. 251-270.

Van Braun, J. (2007), "The world food situation: new driving forces and required actions. IFPRI's biannual overview of the world food situation", *CGIAR Annual General Meeting*, Beijing, [in Chinese].

Van Campenhout, B. (2017), "There is an app for that? The impact of community knowledge workers in Uganda", *Information, Community and Society*, Vol. 20 No. 4, pp. 530-550.

Wang, Q., Li, F., Yu, J., Fleskens, L. and Ritsema, C. (2020), "Price decline, land rental markets and grain production in the North China Plain", *China Agricultural Economic Review*, Vol. 13 No. 1, pp. 124-149.

Wong, J. and Huang, Y. (2012), "China's food security and its global implication", *China: An International Journal*, Vol. 10 No. 1, pp. 113-124.

World Bank (2008), *World Development Report 2008: Agriculture for Development*, World Bank, Washington, District of Columbia.

Wu, Y., Xi, X., Tang, X., Luo, D., Gu, B., Lam, S.K., Vitousek, P.M. and Chen, D. (2018), "Policy distortions, farm size, and the overuse of agricultural chemicals in China", *Proceedings of the National Academy of Sciences*, Vol. 115 No. 27, pp. 7010-7015.

Xu, Z. (2020), "Farm size, capitalism, and overuse of agricultural chemicals in China", *Capitalism Nature Socialism*, Vol. 31 No. 3, pp. 59-74.

Yu, X. and Zhao, G. (2009), "Chinese agricultural development in 30 years: a literature review", *Frontiers of Economics in China*, Vol. 4 No. 4, pp. 633-648.

Zhang, W., Cao, G., Li, X., Zhang, H., Wang, C., Liu, Q., Chen, X., Cui, Z., Shen, J., Jiang, R. and Mi, G. (2016), "Closing yield gaps in China by empowering smallholder farmers", *Nature*, Vol. 537 No. 7622, pp. 671-674.

Appendix
The Appendix file for this article can be found online.

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