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Adoption of organic soil amendments and its impact on farm performance: evidence from wheat farmers in China*

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This study examines the determinants of adoption of organic soil amendments (OSAs) such as organic fertiliser and farmyard manure and its impact on crop yields and net returns, using household survey data of 558 wheat farmers in China. We employ an endogenous switching regression model to account for selection bias stemming from both observable and unobservable factors. The empirical results show that household size, dependency ratio, machine ownership and non-paid labour are main factors that determine farmers' decision to adopt OSA, and the OSA adoption has a positive and statistically significant impact on wheat yields and net returns. In particular, the treatment effects of OSA adoption are to increase wheat yields and net returns by appropriately 22 and 24 per cent, respectively. Moreover, disaggregated analysis by farm size reveals that large-scale households tend to obtain higher wheat yields and net returns than their small-scale counterparts.

Key words: impact evaluation, net returns, organic soil amendments, wheat yields.

JEL classifications: C83, D24, F61, O13

1. Introduction

Soil depletion, occurring both nationally and globally, has posed a wide range of threats to the environment, sustainable agriculture development and food security (Abdulai and Huffman, 2014; Donkor *et al.*, 2019; Krah *et al.*, 2019; Fontes, 2020). For example, land degradation may cause climate change when soil carbon and nitrous oxide on the degraded land is released into the atmosphere. The degraded land usually requires a high level of investment in productivity-enhancing inputs (e.g. agrochemicals) to maintain land productivity. However, this increases production costs and makes smallholder farmers in rural areas more vulnerable, especially those who primarily rely on farm income for their livelihoods (Deng and Li, 2015; Marenya and Barrett,

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2009; Wolka *et al.*, 2018). Therefore, it is of necessity to promote sustainable soil-improving practices to mitigate the adverse effects associated with land degradation.

A growing number of studies have highlighted the positive effects associated with the adoption of sustainable soil-improving practices (e.g. Adolwa *et al.*, 2019; Dey *et al.*, 2010; Di Falco *et al.*, 2011; Issahaku and Abdulai, 2020; Kassie *et al.*, 2009; Teklewold *et al.*, 2013; Wolka *et al.*, 2018). For example, Issahaku and Abdulai (2020) found that adoption of soil and water conservation practices significantly increases crop revenues and reduces riskiness in crop production in Ghana. Adolwa *et al.* (2019) examined the impact of integrated soil fertility management (ISFM) in Ghana and Kenya and found that ISFM adoption could increase maize yields by 16–27 per cent. Organic soil amendments (OSAs)[1] such as organic fertiliser and farmyard manure have been identified as cores of soil-improving practices in land management (Xu *et al.*, 2014; Hassen, 2018; Hoover *et al.*, 2019; Zhuang *et al.*, 2019; Chen *et al.*, 2020), because OSA adoption helps build soil nutrition, increase organic matter and restore soil fertility on the degraded land.[2] For example, Xu *et al.* (2014) found that adoption of organic fertiliser either individually or combined with chemical fertiliser could increase the soil nutrients and slow the rate of de-mineralisation. Zhuang *et al.* (2019) found that substituting compound chemical fertiliser with farmyard manure significantly decreases the loss of nitrogen nutrient components by around 58-75 per cent. The study conducted by Hoover *et al.* (2019) shows that compared with chemical fertiliser, application of poultry manure significantly improves organic matter in the soil.

The objectives of this study are to investigate the determinants of organic soil amendment (OSA) adoption and to estimate the effects of OSA adoption on farm performance. Although previous studies have emphasised the significant role of OSA adoption in recovering degraded soil and improving land productivity (e.g. Hassen, 2018; Hoover *et al.*, 2019; Komarek and Msangi, 2019), the adoption rate of OSA remains quite low. Hassen (2018) noted that only 31 per cent of farmers had adopted farmyard manure in Ethiopia. Thus, understanding the factors that influence farmers' decision to adopt OSA is essential as it can help policymakers identify drivers of adoption and then implement targeted policy interventions to promote farmers' adoption. We measure farm performance using crop yields and net returns. Net return is a meaningful indicator of farm performance as it

[1] A variety of organic amendments such as animal and green manures, compost, nematocidal plants, proteinases wasters and organic fertiliser has been identified and used to improve soil fertility and structure in many developing and transition countries. Following Ma *et al.* (2018a), in the present study organic soil amendments refer to organic fertiliser and/or farmyard manure adopted on farms by wheat farmers in China.

[2] Like chemical fertiliser, farmyard manure may also pose a risk to soil depletion and cause substantial pollution of ecosystems if it is applied at rates that exceed crop requirements (Guo *et al.*, 2018; Ingold *et al.*, 2015). For example, Guo *et al.* (2018) found that long-term animal manure application may degrade soil structure because of the high salt content.

highlights the benefits by taking production costs into account. Some studies have used gross farm income as an indication of the income effect of OSA adoption (e.g. Komarek and Msangi 2019; Arslan *et al.*, 2017), and it is incomplete and problematic because higher gross farm income may be achieved from higher production costs.

We make two significant contributions to the literature on innovative technology adoption. First, we employ an endogenous switching regression (ESR) model to address the selection bias issue associated with OSA adoption. Because farmers select themselves (self-selection) to be OSA adopters or nonadopters, selection bias issue occurs and failing to address such an issue would generate biased estimates (Abdulai and Huffman, 2014; Fontes, 2020; Lokshin and Sajaia, 2004; Ma and Abdulai, 2016). Specifically, the ESR model can mitigate self-selection bias issues stemming from both observable factors (e.g. age, education, household size and farm size) and unobservable factors (e.g. farmers' innate abilities and motivations to improve soil fertility) (Kumar *et al.*, 2020; Li *et al.*, 2020). Some studies have explored the impacts of OSA adoption (Dey *et al.*, 2010; Di Falco *et al.*, 2011; Wolka *et al.*, 2018), without taking into account the selection bias issue. For example, Dey *et al.* (2010) found that the application of organic fertiliser contributes to an increase in crop yields, while Di Falco *et al.* (2011) noted that the application of manure exerts a positive and significant impact on food productivity in Ethiopia.

Second, we investigate the heterogeneous effects of OSA adoption on wheat yields and net returns by selected quantiles of farm size. Unlike previous studies that only estimate the homogenous productivity and income effects of adoption of soil-improving practices (e.g. Adolwa *et al.*, 2019; Singha, 2019), our heterogeneous effects estimations could provide more valuable information that can be used for designing appropriate policy and development programs, aimed at reducing productivity and income inequalities among farmers with different farm size.

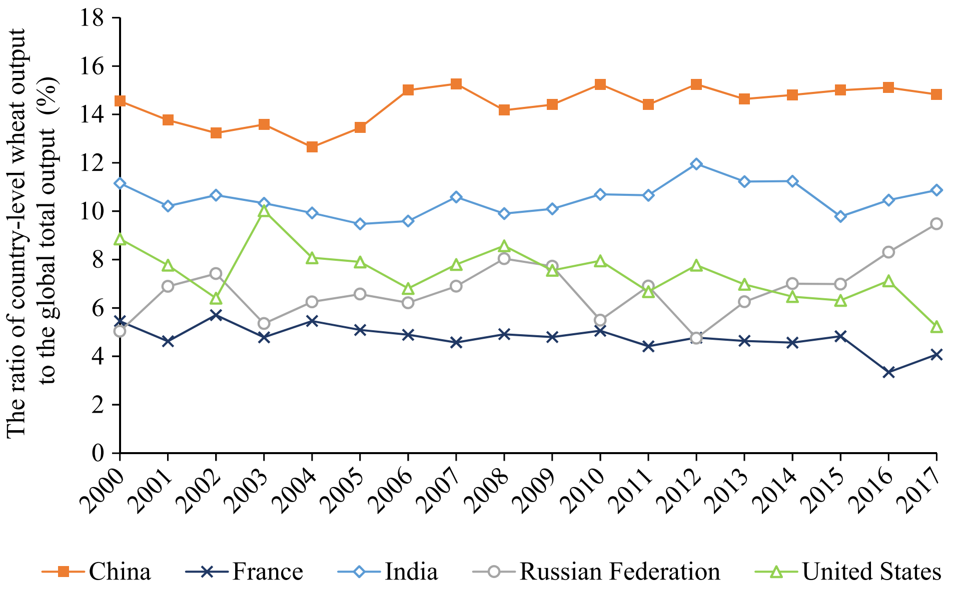
The rest of the paper is organised as follows: Section 2 provides an overview of wheat production in China. Section 3 outlines the analytical framework and empirical strategy. Data and descriptive statistics are presented and discussed in Section 4. Section 5 presents and discusses empirical results. The final section draws conclusions and proposes policy implications.

2. Wheat production and agricultural sustainability in China

China is by far the largest wheat-producing country in the world (Figure 1). In 2017, the total output of wheat was 134.3 million tons (i.e. around 15 per cent of the world's total wheat output), followed by India (98.51 million tons), Russian Federation (85.86 million tons), United States (47.37 million tons) and France (36.92 million tons) (FAOSTAT). Wheat is mainly cultivated in Henan, Shandong, Anhui, Hebei and Jiangsu provinces of China (CRSY, 2019).

Despite being the largest wheat producer in the world, China's wheat production is threatened by chemical fertiliser overuse and low yields (Pan *et al.*, 2017; Li *et al.*, 2019). Chemical fertiliser use in wheat production in China was 371.07 kg/hectare in 2017, representing almost four times the average world level (101.76 kg/hectare) (FAOSTAT). The negative effect of chemical fertiliser use, such as deterioration in soil properties, increase in soil acidifications and depletion of nutrient stocks, has accelerated land degradation (Holden and Lunduka, 2012; Huang and Jiang, 2019; Wolka *et al.*, 2018). Deng and Li (2015) show that due to the lack of organic matter in the soil and overuse of chemical fertiliser, more than 50 per cent of cultivated land has experienced land degradation in China. Moreover, wheat yields in China are relatively low, compared with other wheat-producing countries in the world. In 2017, wheat yields in China were 5.48 tons/hectare (ranking 20th globally), which are higher than the average world level (3.36 tons/hectare) but significantly lower than that in Ireland (10.17 tons/hectare), New Zealand (9.86 tons/hectare) and Netherlands (9.09 tons/hectare) (FAOSTAT). To ensure food security and achieve the 'Zero Hunger' goal of the United Nations, it is of importance to invest in sustainable agricultural production technologies and increase wheat productivity.

The Chinese government has implemented a series of policies and programs to accelerate the dissemination of sustainable agricultural practices



Source: FAOSTAT

Figure 1 The ratio of top five countries' wheat output to the total global output between 2000 and 2017. Source: FAOSTAT. [Colour figure can be viewed at wileyonlinelibrary.com] since 2015, aimed at reducing chemical fertiliser use, improving soil fertility and increasing land productivity. One of these programs is to encourage investment in organic soil amendments (e.g. organic fertiliser or farmyard manure) in crop production. By doing so, the government has entrusted agricultural cooperatives to play a role, because cooperative organisations enable to help smallholder farmers better access information associated with OSA and complementary agronomic practices through collective actions. The existing literature has revealed that cooperative memberships enable to increase the probability of agricultural technology adoption (Ma *et al.*, 2018a; Zhang *et al.*, 2020). Moreover, farmers who apply organic fertiliser can receive a subsidy of 200–300 yuan (equivalent to 29–44 USD) per ton of fertiliser in some eastern provinces, like Zhejiang and Shandong provinces.

3. Analytical framework and empirical strategy

3.1 Analytical framework

OSA adoption can affect yields and net returns of wheat production. A simple framework of potential pathways is illustrated in Figure 2. The first pathway shows that OSA affects wheat yields by helping build in soil nutrients and improve soil fertility, which also contributes to an increase in net returns. Although it takes time to build up nutrient levels, the OSA adoption still has a short-run immediate, but potentially small, effect on soil nutrients and fertility. The positive relationship between OSA adoption and soil remediation has been reported in both short-run and long-run studies (Hoover *et al.*, 2019; Zhuang *et al.*, 2019; Chen *et al.*, 2020). The second pathway reveals that OSA adoption can influence net returns by affecting production costs. OSA adoption in crop production is expected to substitute or complement chemical fertiliser (Hassen, 2018; Bairagi *et al.*, 2019), and thereby, it may affect production costs either positively or negatively. Specifically, if organic soil amendments are applied as complements to chemical fertiliser, OSA adoption tends to increase production costs. However, if organic soil amendments are used to substitute for chemical fertiliser, OSA adoption may decrease production costs. As indicated earlier, this study pays special attention to analysing the impact of OSA adoption on wheat yields and net returns.

Following previous studies (e.g. Abdulai and Huffman, 2014; Donkor *et al.*, 2019; Ma and Abdulai, 2016), a wheat farmer's decision to adopt organic soil amendments can be modelled in a random utility framework. Within this framework, a risk-neutral and utility-maximising wheat farmer is assumed to adopt OSA on their farms if the expected utility gain from adoption (U_i^A) is larger than that obtained from not-adoption (U_i^N), that is $O_i^* = U_i^A - U_i^N > 0$, where O_i^* is a latent variable denoting the utility difference between adoption and non-adoption. We cannot directly observe the actual utility level of O_i^*; however, O_i^* can be expressed as a latent variable function of observable variables as follows:

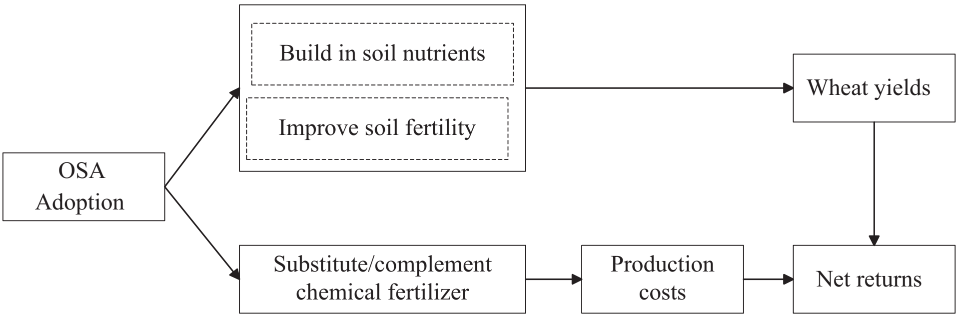


Figure 2 Possible pathways of OSA adoption impacts on wheat yields and net returns.

$$O_i^* = \gamma Z_i + \mu_i, \quad with \quad O_i = \begin{pmatrix} 1, if\, O_i^* > 0 \\ 0, otherwise \end{pmatrix} \tag{1}$$

where O_i is a binary indicator variable that equals one if a wheat farmer adopts OSA, and zero otherwise. Z_i is a vector of explanatory variables (e.g. age, education and farm size); γ is a vector of parameters to be estimated; and μ_i is an error term assumed to be normally distributed with zero mean. The probability of adopting OSA by a wheat farmer i can be specified as:

$$\Pr(O_i = 1) = \Pr(O_i^* > 0) = \Pr(\mu_i > -\gamma Z_i) = 1 - F(-\gamma Z_i) \tag{2}$$

where F is the cumulative distribution function for μ_i. In this study, we assume that μ_i has a normal distribution, and thus, we employ a probit model to estimate Equation (1).

To link the relationship between OSA adoption and farm performance, we assume a rational wheat farmer maximises the expected net returns from wheat production. The net returns function is expressed as follows:

$$\pi_{\max} = PQ(I, Z) - CI \tag{3}$$

where $\pi_{\max}$ is the maximum net returns obtained from wheat production; P is the market price of wheat; is the gross wheat output, which is described by a twice continuously differentiable function of a vector of inputs (I) (e.g. fertiliser, labour and seed) and a vector of explanatory variables (Z); and C is a vector of input prices. The net returns can be described as a function of input and output prices, household and farm-level characteristics and OSA adoption as follows:

$$\pi = \pi(P, C, Z, O) \tag{4}$$

We can get the first-order condition of the maximisation problem from applying Hotelling's Lemma to Equation (3), and this yields a reduced form of the wheat output supply function as follows:

$$Q = Q(P, C, Z, O) \tag{5}$$

Equations (4) and (5) show that net returns and wheat yields depend on inputs and output prices, a vector of explanatory variables, and farmers' OSA adoption decision. In this study, we evaluate the extent to which OSA adoption affects wheat yields and net returns.

3.2 Impact evaluation and selection bias issue

We assume that the outcome variable (wheat yields or net returns) is a linear function of OSA adoption (O_i) and other explanatory variables (X_i) as follows:

$$Y_i = \varphi O_i + \alpha X_i + \varepsilon_i \tag{6}$$

where Y_i refers to a vector of outcome variables including wheat yields and net returns; O_i is a variable indicating farmers' OSA adoption decision as defined above; X_i is a vector of explanatory variables; φ and α are parameters to be estimated; and ε_i is an error term.

In Equation (6), the impact of OSA adoption on wheat yields or net returns is captured by the parameter φ. If the variable representing the OSA adoption (O_i) is exogenously determined, we can employ an ordinary least square (OLS) regression approach to estimate Equation (6). However, as discussed earlier, farmers' OSA adoption decision is not a random assignment but depends on both observable factors (e.g. age, education and household size) and unobservable factors (farmers' innate abilities and motivations). While we know the observable factors, the undeclared factors, which are captured by the error terms, are only known to farmers themselves. If the correlation coefficient between the two error terms does not equal to zero, that is *corr* $(\mu_i, \varepsilon_i) \neq 0$, this would result in biased estimates of parameters in Equation (6).

In order to address the self-selection issue in non-experimental analyses, previous studies have employed various econometric approaches, including propensity score matching (PSM), inverse probability weighted regression adjustment (IPWRA), treatment effects (TE) model and endogenous switching regression (ESR), to conduct unbiased estimates (Adolwa *et al.*, 2019; Li *et al.*, 2020; Ma and Abdulai, 2017; Manda *et al.*, 2018; Singha, 2019). For example, by estimating a PSM model, Singha (2019) found that the adoption of vegetative soil conservation measures significantly increases farm revenue and costs. Manda *et al.* (2018) used the IPWRA and PSM methods to analyse the impact of improved maize varieties on food security in eastern Zambia, and they found that food security is positively and significantly associated with the adoption of improved maize variety. It needs to be noted here that both the PSM and IPWRA approaches are unable to address the selection bias issue arising from unobservable factors. Although the TE model can address selection bias issues originating from both observable and unobservable factors, it is unable to estimate factors affecting the outcome variables, respectively, for the treated group and control group (Ma *et al.*, 2020; Ma and Abdulai, 2017). In comparison, the ESR model has two significant advantages over other approaches: (1) it can eliminate selection bias originating from both observed and unobserved factors, overcoming the drawback of PSM and IPWRA methods; and (2) it helps identify factors that affect wheat yields and net returns, respectively, for OSA adopters and nonadopters, overcoming the drawback of the TE model. Thus, it is employed in this study. As a robustness check, we also present the results estimated from the TE model.

3.3 The ESR model

3.3.1 Identifying determinants of OSA adoption and determinants of outcome variables

The ESR model uses the full information maximum likelihood (FIML) estimation approach to estimate the effects of a treated variable (i.e. OSA adoption in this study) in two stages (Abdulai and Huffman, 2014; Donkor *et al.*, 2019; Li *et al.*, 2020; Lokshin and Sajaia, 2004). In the first stage, the determinants of OSA adoption, which are captured by Equation (1), are investigated by estimating a probit model. In the second stage, the determinants of the outcome variables (wheat yields and net returns) are regressed separately for OSA adopters and nonadopters, as shown in Equations (7a) and (7b):

$$\text{Re}gime\,1\,(Adopters): Y_{iA} = \alpha_{iA}X_{iA} + \varepsilon_{iA} \quad if \quad O_i = 1 \tag{7a}$$

$$Regime\,2\,(Nonadopters): Y_{iN} = \alpha_{iN}X_{iN} + \varepsilon_{iN} \quad if \quad O_i = 0 \tag{7b}$$

where Y_{iA} and Y_{iN} are outcome variables representing wheat yields and net returns for OSA adopters and nonadopters, respectively; X_{iA} and X_{iN} refer to a vector of exogenous variables; α_{iA} and α_{iN} are parameters to be estimated; and ε_{iA} and ε_{iN} are error terms.

The selection bias arising from observable factors is captured by the variables X_{iA} and X_{iN} in Equations (7a) and (7b). The ESR model addresses the selection bias arising from unobservable factors by calculating Inverse Mill Ratios (IMRs) after estimating Equation (1) and including them in Equations (7a) and (7b). Thus, the Equations (7a) and (7b) can be rewritten as follows

$$Regime\,1\,(Adopters): Y_{iA} = \alpha_{iA}X_{iA} + \sigma_{\mu A}\lambda_{iA} + \vartheta_{iA} \quad if \quad O_i = 1 \tag{8a}$$

$$Regime\,2\,(Nonaadopters):\;Y_{iN}=\alpha_{iN}X_{iN}+\sigma_{\mu N}\lambda_{iN}+\vartheta_{iN}\;\;if\;\;O_i=0 \tag{8b}$$

where Y_{iA}, Y_{iN}, X_{iA} and X_{iN} are defined as above; λ_{iA} and λ_{iN} are IMRs, which are used to capture selection bias arising from unobservable factors; $\sigma_{\mu A}$ and $\sigma_{\mu N}$ are the covariance terms, which are defined as $\sigma_{\mu A}=\text{cov}(\mu_i,\varepsilon_{iA})$ and $\sigma_{\mu N}=\text{cov}(\mu_i,\varepsilon_{iN})$, respectively; and ϑ_{iA} and ϑ_{iN} are errors terms with conditional zero means. The selection Equation (1) and the outcome Equations (7a) and (7b) are estimated simultaneously using the FIML estimator. The ESR model uses the correlation coefficients, $\rho_{\mu A}(\sigma_{\mu A}/\sigma_{\mu}\sigma_A)$ and $\rho_{\mu N}(\sigma_{\mu N}/\sigma_{\mu}\sigma_N)$ to identify the existence of selection bias arising from unobservable factors (Abdulai and Huffman, 2014; Kumar *et al.*, 2020; Li *et al.*, 2020). Specifically, selection bias associated with unobservable factors exists if $\rho_{\mu A}$ and/or $\rho_{\mu N}$ is significantly different from zero.

3.3.2 Estimating treatment effects

The estimates of Equation (1), Equations (7a) and (7b) enable us to understand the factors affecting farmers' decision to adopt OSA as well as the factors influencing wheat yields and net returns, respectively, for OSA adopters and nonadopters. To estimate the treatment effects of OSA adoption on wheat yields and net returns, some further calculations are required. Within the ESR framework, the treatment effects can be calculated by comparing the expected values of outcome variables for OSA adopters with the expected values of outcome variables for adopters had they did not adopt. Specifically, in the observable scenario, the expected values of the outcome variables for OSA adopters can be specified as:

$$E[Y_{iA}|O=1]=\alpha_{iA}X_i+\sigma_{\mu A}\lambda_{iA} \tag{9a}$$

In the counterfactual scenario, the expected values of the outcome variables for OSA adopters had they did not adopt can be expressed as:

$$E[Y_{iN}|O=1]=\alpha_{iN}X_i+\sigma_{\mu N}\lambda_{iA} \tag{9b}$$

Following Lokshin and Sajaia (2004) and Kumar *et al.* (2020), the average treatment effects on the treated (ATT), which is the treatment effect of OSA adoption on wheat yields and net returns, can be derived by calculating the difference of outcomes between Equations (9a) and (9b):

$$ATT=E[Y_{iA}|O=1]-E[Y_{iN}|O=1]=X_i(\alpha_{iA}-\alpha_{iN})+\lambda_{iA}(\sigma_{\mu A}-\sigma_{\mu N}) \tag{10}$$

3.3.3 ESR model identification

The ESR model allows an overlap of Z_i in selection Equation (1) and X_i in outcome Equations (7a) and (7b). However, for identification purposes, at least one variable that served as identifying instrument in Z_i in selection Equation (1) should not appear in X_i in the outcome Equations (7a) and (7b) (Kumar *et al.*, 2020; Li *et al.*, 2020; Lokshin and Sajaia, 2004; Ma and Abdulai, 2016). A valid instrument is expected to influence farmers' OSA adoption decisions but does not directly affect outcome variables. In this study, a technical training variable, which measures the number of technical training sessions received by farmers in 2018, is employed as an identifying instrument. Previous studies have shown that participation in soil-improving practice training stimulates farmers' adoption behaviour (Chesterman *et al.*, 2019; Krah *et al.*, 2019). It is envisaged that OSA adoption is conditional on farmer's perception of the consequences of chemical fertiliser overuse and the importance of investing in organic soil amendments. Farmers may become more cognisant of the benefits associated with OSA and are more willing to adopt it if they receive more related information from technical training. However, technical training variable is not expected to affect the outcome variables directly. Following previous studies (Manda *et al.*, 2019; Fontes, 2020), we run a probit model for OSA adoption and two OLS regression models for outcome equations, respectively, for wheat yields and net returns, to check the validity of the employed instrumental variable. As shown in Table S1 in the Appendix S1, the coefficient of technical training variable is significantly positive in the adoption equation but shows no significant effects in the outcome equations. These findings indicate that the technical training variable is a valid instrument.

4. Data, variables and descriptive statistics

4.1 Data

The data used in this study were collected from a farm household survey, conducted between June and July 2019 in rural China. We used a multistage random sampling technique to select sample households. In the first stage, three major wheat-producing provinces including Shandong, Henan and Anhui provinces were purposively selected (see Figure S1 in the Appendix S1). These three provinces are located in the Huang-Huai-Hai Plain, which is identified as a main region for wheat production in China because of favourable climate and ecological conditions. In 2017, these three provinces produced more than half of the total wheat output (around 58 per cent) in China (CRSY, 2019). In the second stage, two cities were randomly selected from each province. These include Linyi and Zaozhuang in Shandong, Xinyang and Zhumadian in Henan, and Suzhou and Huaibei in Anhui (see Figure S1). In the third stage, two to three towns were randomly selected in each selected city.[3] In the fourth stage, two to three villages were

[3] Towns and cities are administrative division units used in China, and they are made up of both rural and urban populations.

randomly chosen in each selected town. Finally, between 10 and 30 households, including both OSA adopters and nonadopters in each village, were randomly selected using the household lists provided by village heads. The sampling procedure helped us obtain 558 households in total, including 87 OSA adopters and 471 nonadopters.[4]

We use Cochran's formula to determine the sample size due to a lack of information on the population of wheat farmers in the survey regions (Cochran, 1977; Zhou *et al.*, 2020). Cochran's formula is expressed as $n_0 = pqZ^2/e^2$, where we assume a P-value of 0.5, a confidence level q of 95%, a Z-value of 1.96 and margin of error e of 5%. Thus, we can determine a minimum sample size of 385 ($n_0 = (0.5)(0.95)(1.96)^2/(0.05)^2$). As detailed in Table 1, the present paper relied on a sample size of 558 respondents to ensure precision.

Sample households were interviewed face-to-face by enumerators who spoke both Mandarin and local dialects. A structured and pretested questionnaire was used to collect detailed information on demographic and socioeconomic characteristics (e.g. household head's age and education, relationship with relatives), farm characteristics (e.g. soil types and farm size), income, inputs (e.g. chemical fertiliser, organic fertiliser, farmyard manure, pesticides and machinery use), wheat yields and sales price of wheat. Before the formal survey, we modified the questionnaire based on the feedback collected from the pre-survey and trained the enumerators.

4.2 Key variable measurement

The outcome variables in this study include wheat yields and net returns. In particular, wheat yields refer to wheat yields per mu (1 mu = 1/15 hectare), while net returns are calculated as the difference between the gross income of wheat production and variable costs per mu. The variable costs include expenses on seed, pesticides, chemical fertiliser, organic soil amendments (i.e. farmyard manure and organic fertiliser), machinery, irrigation and hired labour. The treatment variable refers to OSA adoption, which is a binary variable identifying whether or not a farmer has adopted OSA (organic fertiliser and/or farmyard manure) in wheat production in 2018. The variable takes a value of one for OSA adopters and zero for nonadopters, a definition that has been used in previous studies (e.g. Ma *et al.*, 2018a). Farmers can either purchase organic fertiliser from local input markets or buy manure from other farmers who have surplus, or use the manure they produce on their farm. To simplify our analysis, in this study, we focus on whether farmers adopt OSA rather than how farmers obtain it. We draw on previous

[4] During the survey, we gathered information why organic soil amendments are not adopted by farmers, using an open-ended question. Our findings show that several factors have attributed to the non-adoption of the technology, including underdeveloped OSA markets in rural areas, limited perception of the benefits associated with OSA adoption and reduced motivation to feed livestock in backyards.

Table 1 Definition and summary statistics of selected variables

Variable	Definition	Mean	SD
Dependent variables			
Wheat yields	Wheat yields (100 kg/mu)†	4.12	1.18
Net returns	Gross income of wheat production minus variable costs (100 yuan/mu)‡	3.40	3.52
OSA adoption	1 if farmer adopts organic soil amendments (e.g. organic fertiliser and/or farmyard manure) in wheat production, 0 otherwise	0.16	0.36
Independent variables			
Age	Age of household head (years)	56.50	11.22
Gender	1 if household head is male, 0 otherwise	0.60	0.49
Education	Education of household head (years)	4.73	3.84
Marital status	1 if household head is married, 0 otherwise	0.89	0.31
Household size	Number of members in a household (persons)	4.70	2.45
Dependency ratio	Ratio of children (15 years or younger) and elder (65 years or older) to total household size	0.38	0.31
Machine ownership	1 if farmer owns agricultural machine, 0 otherwise	0.81	0.40
Non-paid labour	1 if farmer can get help from relatives during the busy farming seasons, 0 otherwise	0.45	0.50
Farm size	Total farm size for wheat production (mu)	9.07	11.31
Sandy soil	1 if land has sandy soil, 0 otherwise	0.20	0.40
Clay soil	1 if land has clay soil, 0 otherwise	0.20	0.40
Loam soil	1 if land has loam soil, 0 otherwise	0.60	0.49
Distance to market	Distance to the nearest output market (km)	2.22	2.48
Shandong	1 if farmer residents in Shandong province, 0 otherwise	0.48	0.50
Henan	1 if farmer residents in Henan province, 0 otherwise	0.26	0.44
Anhui	1 if farmer residents in Anhui province, 0 otherwise	0.27	0.44
Technical training (IV)	The number of technical trainings received by farmers in 2018	0.18	0.74
Observations		558	

Note: SD refers to standard deviation.
†1 mu = 1/15 hectare.
‡Yuan is Chinese currency (1USD = 6.88 yuan in July 2019).

studies on adoption and impacts of soil-improving practices to identify independent variables (e.g. Abdulai and Huffman, 2014; Abdulai, 2016; Adolwa *et al*., 2019; Fontes, 2020; Issahaku and Abdulai, 2020; Kassie *et al*., 2009; Marenya and Barrett, 2009; Teklewold *et al*., 2013; Tesfaye *et al*., 2016).

4.3 Descriptive statistics

Table 1 presents the definitions and descriptive statistics of the variables used in the analysis. As shown in this table, the average yields and net returns of wheat production were 412 kg/mu and 340 yuan/mu, respectively. The average wheat yields in our sample are higher than the wheat yields at the national level (i.e. 369 kg/mu) (DPNDRC, 2019) because our samples are obtained from three representative provinces of wheat production in China. It can be observed that only 16 per cent of farmers have adopted organic soil amendments in wheat production, indicating a lower rate of OSA adoption among wheat producers. Table S2 in the Appendix S1 reports the number of adopters with different adoption status. It shows that only 18 farmers adopted both organic fertiliser and farmyard manure simultaneously, 35 farmers only adopted organic fertiliser, and 34 farmers only adopted farmyard manure. Table 1 also reveals that the mean age of household heads is 56.50 years, with 4.73 years of schooling on average. The mean land area cultivated for wheat production was 9.07 mu.

Table 2 presents the mean differences in characteristics between OSA adopters and nonadopters. The mean values of the employed variables between these two groups of farmers show statistical differences. Compared with nonadopters, OSA adopters tend to be younger, better educated and have more household members, but they are less likely to own machinery and have a smaller farm size. It also reveals that mean wheat yields and mean net returns for OSA adopters are around 15 and 40 per cent, respectively, higher than those for nonadopters. However, simple descriptive statistics could not be interpreted as the treatment effects of OSA adoption, as they did not account for confounding factors. Thus, it is necessary to estimate the effect of OSA adoption on wheat yields and net returns, using econometric approaches such as the ESR model.

Figure 3 demonstrates the average wheat yields and net returns by selected quantiles of farm size, which show wheat yields and net returns are different among farmers at different quantiles of farm size. Figure 3 shows that for both OSA adopters and nonadopters, an increase in farm size from 25th quantile to 50th quantile and then to 75th quantile, coincides with wheat yields monotonically decreasing while net returns monotonically increasing. In general, the information illustrated in Figure 3 suggests that there may exist heterogeneous effects of OSA adoption on farm performance.

5. Empirical results

The estimated results of the ESR model are presented in Tables 3 and 4. In the lower parts of these two tables, the Wald test statistics for joint independence of the equations show that they are significantly different from zero, suggesting that the three equations are dependent. In addition, the significant correlation coefficients of the error terms (i.e. $\rho_{\mu N}$ in Table 3 and $\rho_{\mu A}$ in Table 4) indicate the presence of selection bias arising from unobservable factors (Abdulai and Huffman, 2014; Kumar *et al.*, 2020; Li *et al.*, 2020; Ma and Abdulai, 2016). These findings confirm the appropriateness of using the ESR model in this study.

In sections below, we firstly discuss the determinants of OSA adoption before discussing the determinants of wheat yields and net returns. Afterwards, the results for the treatment effects and heterogeneous effects

Table 2 Mean differences in characteristics between OSA adopters and nonadopters

Variable	Adopters (87)	Nonadopters (471)	Diff.
Wheat yields	4.64	4.03	0.61***
Net returns	4.48	3.20	1.28***
Age	56.18	56.56	−0.38
Gender	0.64	0.59	0.05
Education	4.97	4.69	0.28
Marital status	0.92	0.89	0.03
Household size	5.07	4.64	0.43
Dependency ratio	0.33	0.39	−0.07*
Machine ownership	0.70	0.83	−0.12***
Non-paid labour	0.54	0.43	0.11*
Farm size	7.13	9.42	−2.30*
Sandy soil	0.20	0.20	−0.01
Clay soil	0.20	0.20	−0.00
Loam soil	0.61	0.60	0.01
Distance to market	2.14	2.23	−0.10
Shandong	0.75	0.43	0.32***
Henan	0.06	0.29	−0.24***
Anhui	0.20	0.28	−0.08

***<0.01, *<0.10.

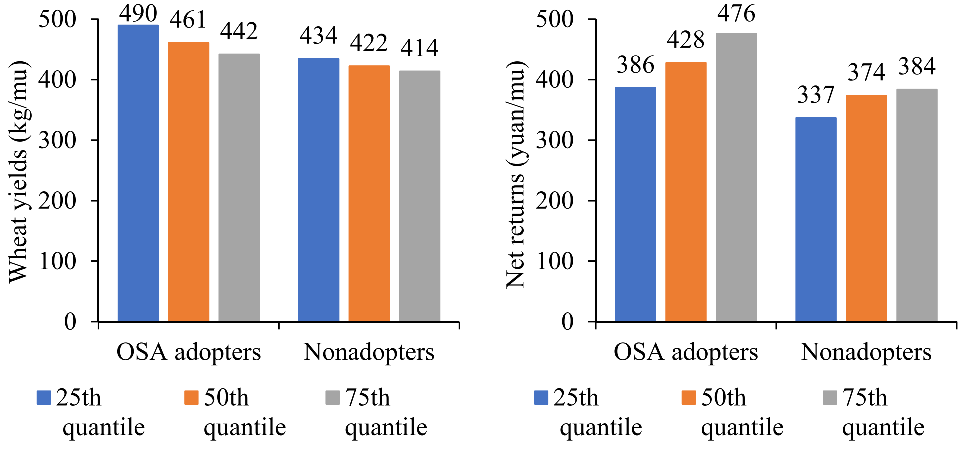


Figure 3 Average wheat yields and net returns by selected quantiles of farm size. [Colour figure can be viewed at wileyonlinelibrary.com]

of OSA adoption are presented and discussed. Finally, we discuss the results of the robustness check.

5.1 Determinants of OSA adoption

The estimates of the determinants of OSA adoption, which are estimated by Equation (1), are presented in the second column of Tables 3 and 4. The coefficients of variables with the same name in the selection specifications in

Table 3 Determinants of OSA adoption and determinants of wheat yields

Variables	Selection	Wheat yields	
		Adopters	Nonadopters
Age	−0.001	0.020	0.001
	(0.007)	(0.008)**	(0.005)
Gender	0.242	−0.111	−0.012
	(0.161)	(0.177)	(0.097)
Education	−0.020	0.064	0.010
	(0.021)	(0.027)**	(0.013)
Marital status	0.064	−0.383	−0.000
	(0.245)	(0.234)	(0.145)
Household size	0.075	−0.007	−0.045
	(0.030)**	(0.049)	(0.019)**
Dependency ratio	−0.431	−0.789	−0.143
	(0.259)*	(0.399)**	(0.174)
Machine ownership	−0.298	0.508	0.007
	(0.160)*	(0.210)**	(0.109)
Non-paid labour	0.303	−0.018	−0.002
	(0.134)**	(0.205)	(0.088)
Farm size	−0.016	−0.027	−0.011
	(0.011)	(0.021)	(0.005)**
Clay soil	0.402	0.607	0.116
	(0.234)*	(0.346)*	(0.154)
Loam soil	0.126	0.404	0.453
	(0.182)	(0.272)	(0.130)***
Distance to market	−0.019	−0.014	−0.005
	(0.025)	(0.031)	(0.018)
Shandong	0.393	0.501	0.526
	(0.167)**	(0.278)*	(0.117)***
Henan	−0.847	−1.416	−0.943
	(0.252)***	(0.516)***	(0.140)***
Constant	−1.285	3.183	3.953
	(0.523)**	(0.730)***	(0.335)***
Technical training (IV)	0.150		
	(0.077)*		
$Ln\sigma_{\mu A}$		−0.285	
		(0.077)***	
$\rho_{\mu A}$		−0.027	
		(0.316)	
$Ln\sigma_{\mu N}$			−0.070
			(0.038)*
$\rho_{\mu N}$			−0.459
			(0.185)**
Wald test χ^2	6.180** (P−value = 0.045)		
Log-likelihood	−930.093		
Observations	558	558	558

Note: Robust standard errors are presented in parentheses; ***<0.01, **< 0.05, *<0.10.
Wheat yields are measured in 100 kg/mu.
The reference region is Anhui. The reference soil is sandy soil.

Tables 3 and 4 are interpreted together because the variables have similar effects on OSA adoption. In both selection specifications, the household size variable exerts a positive and statistically significant effect on OSA adoption,

Table 4 Determinants of OSA adoption and determinants of net returns

Variables	Selection	Net returns	
		Adopters	Nonadopters
Age	−0.001	0.032	0.009
	(0.007)	(0.035)	(0.014)
Gender	0.234	−0.014	−0.168
	(0.161)	(0.665)	(0.300)
Education	−0.018	0.161	0.057
	(0.020)	(0.098)	(0.039)
Marital status	0.036	−0.487	−0.217
	(0.241)	(1.030)	(0.443)
Household size	0.065	0.011	−0.121
	(0.029)**	(0.120)	(0.054)**
Dependency ratio	−0.431	−3.083	−0.516
	(0.260)*	(1.225)**	(0.514)
Machine ownership	−0.303	2.314	0.266
	(0.161)*	(0.800)***	(0.360)
Non-paid labour	0.289	−0.502	−0.056
	(0.135)**	(0.604)	(0.284)
Farm size	−0.013	0.074	−0.003
	(0.012)	(0.067)	(0.007)
Clay soil	0.372	1.505	0.739
	(0.236)	(1.032)	(0.517)
Loam soil	0.123	1.729	1.483
	(0.184)	(0.812)**	(0.464)***
Distance to market	−0.017	−0.271	0.021
	(0.026)	(0.165)	(0.053)
Shandong	0.390	1.166	0.521
	(0.169)**	(0.886)	0.383)
Henan	−0.817	−3.704	−3.468
	(0.256)***	1.588)**	(0.424)***
Constant	−1.229	1.602	2.939
	(0.520)**	(3.296)	(1.109)***
Technical training (IV)	0.177		
	(0.069)**		
$Ln\sigma_{\mu A}$		1.015	
		(0.091)***	
$\rho_{\mu A}$		−0.472	
		(0.248)*	
$Ln\sigma_{\mu N}$			1.088
			(0.047)***
$\rho_{\mu N}$			−0.114
			(0.103)
Wald test χ^2	4.826* (p−Value = 0.090)		
Log-likelihood	−1,594.868		
Observations	558	558	558

Note: Robust standard errors are presented in parentheses; ***<0.01, **<0.05, *<0.10.
Net returns are measured in 100 yuan/mu.
The reference region is Anhui. The reference soil is sandy soil.

suggesting that large household size increases the probability of OSA adoption. The finding is consistent with Tesfaye *et al.* (2016) and Fontes (2020), who found that household size is significantly correlated with the adoption of soil-improving practices in Ethiopia. Larger households are usually endowed with more labour, and they may earn more income that can be used to purchase organic soil amendments. The coefficients of the variable representing dependency ratio are negative and significantly different from zero, indicating that a higher dependency ratio is associated with a lower probability of OSA adoption. This finding is in line with the results by Arslan *et al*. (2017) and Manda *et al*. (2018), who highlighted that dependency ratio is an important constraint in adopting organic fertiliser and other advanced technologies in African counties such as Tanzania and Zambia. Farmers who have to take care of their (younger and/or older) family members may potentially face both labour and financial constraints, making them unable to invest in OSA.

The coefficients of machine ownership variable are negative and statistically significant, suggesting that farmers who own agricultural machines are less likely to adopt OSA. The plausible reason is that machines owned by the majority of farmers are not for OSA application purposes. Unlike dry chemical fertiliser that can be easily applied by machines, organic soil amendment, particularly farmyard manure, is usually applied manually because of its irregular shape and high humidity. Our finding suggest that farmers who are more mechanised tend to rely more on chemical fertiliser, and those who are less mechanised are more likely to adopt OSA, a finding that echoes with previous studies (Nepal and Thapa, 2009). The coefficients of the variable representing non-paid labour are positive and significantly different from zero, indicating that access to relatives' help is an essential driver of OSA adoption. Labour is an integral part that facilitates innovative agricultural technology adoption. Access to non-paid labour provided by relatives can motivate farmers to adopt OSA. Our findings highlight that relatives' help during the busy farming seasons may facilitate OSA adoption as it enables farmers to release labour constraints. The significant coefficients on regional dummy variables indicate that relative to farmers in Anhui (reference group), those producing wheat in Shandong are more likely to adopt OSA while those in Henan are less likely to adopt it. The findings suggest the presence of unobserved cluster and region-specific factors (e.g. regional socioeconomic and climate conditions and regional institutional arrangements related to agricultural subsidies) that affect farmers' decision to adopt OSA. Finally, the coefficients of identifying instrument variable are positive and significantly different from zero, suggesting that the probability of OSA adoption significantly increases with an increase in the number of technical training sessions received by farmers.

5.2 Determinants of wheat yields and net returns

The estimates of the determinants of wheat yields and net returns for both OSA adopters and nonadopters, which are estimated using the outcome Equations (7a) and (7b), are presented in the third and fourth columns of

Tables 3 and 4, respectively. The age variable shows a positive and statistically significant impact on wheat yields for OSA adopters, indicating that elder OSA adopters tend to obtain higher wheat yields than their younger counterparts. The result may reflect the fact that rich experience in farm management is positively associated with higher crop yields. The positive and significant coefficient of the education variable suggests that an increase in education level tends to increase wheat yields among OSA adopters. The finding of the positive relationship between education and wheat yields is in line with the finding of Abdulai and Huffman (2014), who showed that good knowledge and a firm understanding of the soil and water conservation technology helps increase rice yields in Ghana. In an investigation for Zambia, Abdulai (2016) also found a similar result that education exerts a positive and significant impact on maize outputs among adopters of conservation agriculture technology.

Household size shows a significantly negative impact on wheat yields and net returns among nonadopters, suggesting that farmers with larger household size tend to obtain lower yields and net returns from wheat production. Kassie *et al.* (2008) also found that family size significantly lowers crop production value for nonadopters of soil conservation technology in Ethiopia. The ownership of the agricultural machine tends to have a positive and significant impact on wheat yields and net returns for OSA adopters, but no significant impacts for nonadopters. Farm machine use in wheat production substitutes farm labour and improves production efficiency (Ma *et al.*, 2018b), which reduces production costs and increases crop production, and finally contributes to an increase in farm income gains.

The variable representing dependency ratio has a negative and statistically significant impact on wheat yields and net returns for OSA adopters. The finding suggests that a lower labour ratio is associated with lower wheat yields and net returns, a finding that is consistent with Kumar *et al.* (2018), who showed that the high dependency ratio of dairy farmers decreases milk yields in India. The farm size variable exerts a negative and statistically significant impact on wheat yields for nonadopters, indicating that OSA nonadopters cultivating larger farms obtain lower wheat yields. The inverse relationship between farm size and crop productivity is in line with previous studies such as Dey *et al.* (2010) for Malawi and Ma and Abdulai (2016) for China.

Soil variables and regional dummy variables tend to have different impacts on wheat yields and net returns for OSA adopters and nonadopters. Relative to land cultivation on sandy soil (reference group), land cultivation on clay soil significantly increases wheat yields for OSA adopters, while cultivating land on loam soil significantly increases net returns for both OSA adopters and nonadopters. The significant influence of soil variables indicates that environmental variables should not be omitted for the unbiased estimates of the productivity and income effects of OSA adoption. Compared with wheat farmers in Anhui (reference group), both OSA adopters and nonadopters in

Shandong tend to obtain higher wheat yields, while their counterparts in Henan tend to obtain lower wheat yields and net returns.

5.3 Results of treatment effects and heterogeneous effects estimations

The estimates for the average treatment effects on the treated (ATT), which show the effects of OSA adoption on wheat yields and net returns, are presented in Table 5. Compared with the simple mean differences in Table 2, the ATT estimates in Table 5 control for confounding factors that generate selection bias issues. In general, our results show that OSA adoption has a positive and statistically significant impact on wheat yields and net returns. Specifically, we show that the treatment effects of OSA adoption are to significantly increase wheat yields and net returns by appropriately 22 and 24 per cent, respectively. The findings are largely consistent with previous studies (Arslan *et al.*, 2017; Hoover *et al.*, 2019), which have highlighted the positive relationship between adoption of soil-improving practices and farm performance.

Figure 3 has indicated the presence of potential heterogeneous effects of OSA adoption among farmers at different quantiles of farm size. Here, we empirically tested it and presented the results in Table 6. Generally, our estimates confirm the impacts of OSA adoption are heterogeneous. Our estimates in Table 6 suggest that large-scale farmers tend to obtain higher wheat yields and net returns from OSA adoption. We show that OSA adoption is to increase wheat yields by around 21, 19 and 23 per cent for farmers at the 25^{th}, 50^{th} and 75^{th} quantiles of farm size, respectively, a finding indicating a ‘U-shaped relationship’ between farm size and wheat yields. OSA adoption affects net returns monotonically, which increases net returns by around 8 per cent at the 25^{th} quantile, 19 per cent at the 50^{th} quantile and 35 per cent at the 75^{th} quantile.

5.4 Robustness check

To check the robustness of the ESR model estimates, we also examined the impact of OSA adoption on wheat yields and net returns using a treatment

Table 5 Average treatment effects of OSA adoption on wheat yields and net returns

Outcome	Mean outcomes		ATT	*t*-Value	Change (%)
	Adopters	Nonadopters			
Wheat yields	4.64 (0.61)	3.80 (0.61)	0.84***	21.35	22.11
Net returns	4.48 (2.14)	3.61 (1.37)	0.87***	4.79	24.10

Note: Robust standard errors are presented in parentheses; ***<0.01.
ATT refers to average treatment effects on the treated.
Wheat yields and net returns are measured in 100 kg/mu and 100 yuan/mu, respectively.

effects model. Like the ESR model, the treatment effects model addresses selection bias generated by both observable and unobservable factors (Ma *et al.*, 2020; Ma and Abdulai, 2017). Another advantage of the treatment effects model is that it estimates a direct impact of OSA adoption on outcome variables of interest. The results (Table S3 in the Appendix S1) show that the coefficients of the OSA adoption variable are positive and statistically significant, suggesting that OSA adoption increases both wheat yields and net returns. The findings confirm the positive relationship between OSA adoption and farm performance in wheat production.

6. Conclusions and policy implications

Although OSA adoption enables to build in soil nutrients and improve soil fertility, little is known on how and to what extent OSA adoption is associated with farm performance. To address this research gap, in this study, we examined the impact of OSA adoption on wheat yields and net returns, utilising 2019 survey data collected from 558 wheat farmers in China. We employed the ESR model as an econometric approach to control for the selection bias issues stemming from both observable and unobservable factors.

The results estimated by the ESR model did suggest the presence of selection bias. After controlling for the bias, we showed that OSA adoption increases wheat yields by 22 per cent and net returns by 24 per cent. The positive impacts of OSA adoption on wheat yields and net returns were confirmed by the results estimated by the treatment effects model. Moreover, disaggregated analyses by farm size showed that large-scale households tend to obtain higher wheat yields and net returns than their small-scale counterparts.

Table 6 Average treatment effects of OSA adoption on wheat yields and net returns by selected quantiles of farm size

Outcome	Category	Mean outcomes		ATT	*t*-Value	Change (%)
		Adopters	Nonadopters			
Wheat yields	25th	4.82 (0.62)	3.99 (0.49)	0.83***	10.97	20.80
	50th	4.69 (0.38)	3.96 (0.35)	0.74***	7.98	18.69
	75th	4.44 (0.62)	3.60 (0.70)	0.84***	13.36	23.33
Net returns	25th	3.98 (2.38)	3.95 (1.18)	0.03	0.07	7.59
	50th	4.46 (1.52)	3.77 (0.72)	0.70**	2.53	18.57
	75th	4.39 (2.06)	3.25 (1.67)	1.14***	6.16	35.08

Note: Robust standard errors are presented in parentheses; ***<0.01, **<0.05, *<0.10.
ATT refers to average treatment effects on the treated.
Wheat yields and net returns are measured in 100 kg/mu and 100 yuan/mu, respectively.

Our results also provide significant insights into the factors that affect farmers' decision to adopt OSA as well as the factors influencing wheat yields and net returns. We showed that household size, dependency ratio, machine ownership and non-paid labour are main factors that determine farmers' decision to adopt OSA. With respect to the factors that influence wheat yields and net returns, we showed that in addition to OSA adoption, household heads' age, education and machine ownership mainly affect wheat yields and net returns.

Land degradation has accelerated globally during the 20th century due to extreme weather events (e.g. droughts and coastal surges which salinate land), urbanisation, deforestation, and increasing and combined pressures of agricultural and livestock production (e.g. over-cultivation, overgrazing and forest conversion). Thus, our findings have important implications for policymakers not only in China but also in other countries in their efforts to promote innovative technologies for achieving sustainable development goals of agricultural production. The findings that OSA adoption significantly increases wheat yields and net returns indicate that the government should make efforts to enhance farmers' awareness of the benefits associated with OSA to increase its adoption rate in crop production. In practice, the government could consider collaborating with agricultural cooperatives for technology dissemination because cooperatives enable to gather and train rural farmers through collective actions. Ownership of agricultural machinery is negatively associated with OSA adoption, while we show that only 22 per cent of sample farmers own machines for fertilisation purposes. Thus, there is a need that the government helps smallholder farmers access and use machines for fertilisation application, which indeed may increase their OSA adoption.

Our analysis is based on cross-sectional data collected from 558 wheat farmers in China. OSA alters soil structure and improves soil quality over time. Due to data limitations, we are unable to capture the dynamic effects of OSA adoption on farm performance. However, we believe this is a promising area to investigate in the future when the required panel data are available. Future studies may also investigate the temporal patterns of OSA adoption to find out whether there exist differences in farm performance indicators between farmers who have always adopted OSA and those who just decide to adopt the technology in the recent past. Organic soil amendments are promoted in some countries to partially or fully substitute chemical fertilisers, so analysing the substitution effects of OSA adoption on chemical fertiliser use focusing on other crops and other regions is another interesting strand for future studies.

Conflict of interests

There is no conflict of interest.

Data availability statement

The data that support the findings of this study are available from the leading author, Hongyun Zheng, upon reasonable request.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Map of sample provinces and cities.
Table S1. Parameter estimates for the validity test of the employed instrument.
Table S2. The number of OSA adopters with different adoption status.
Table S3. Impact of OSA adoption on wheat yields and net returns.