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Scaling-up agricultural technologies: who should be targeted?

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Abstract

The effects of agricultural technology adoption on farm performance have been studied extensively but with limited information on who should be targeted during scaling-up. We adopt the newly defined marginal treatment effect approach in examining how farmers' resource endowment and unobserved factors influence the marginal benefits of adopting sustainable intensification (SI) practices. We estimate both the marginal and average benefits of adopting SI practices and predict which marginal farm household entrants will benefit the most at scale. Findings indicate that farmers' resource endowment and unobserved factors affect the marginal benefits of adopting SI practices, which also influence maize yield and net returns among adopters. Finally, results imply that scaling up SI practices will favour farm household entrants associated with the lowest probability of adoption based on observed socioeconomic characteristics.

Keywords: adoption, agricultural technologies, marginal treatment effect, sustainable intensification practices, scaling-up

JEL classification: C21, D60, O33

1. Introduction

The literature on technology adoption has identified lack of information (Ashraf, Giné and Karlan, 2009), poor road network (Karlan *et al.*, 2014), inadequate use of inorganic fertilizer (Duflo, Kremer and Robinson, 2011), lack of access to new inputs (Emerick and Dar, 2021), and differences in farming systems (Giller *et al.*, 2009; Giller *et al.*, 2011) as some of the causes for the poor adoption of agricultural technologies and practices.

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However, less documented are the scaling-up methods and the types of marginal farm household entrants that need to be targeted during the scaling-up process.

As part of the testing and dissemination of sustainable intensification (SI) practices in northern Ghana, we explore the heterogeneous effects of farmers' resource endowment and unobserved factors (e.g. technical and managerial skills) on the marginal benefits of SI practices adoption, estimate marginal and average effects of SI practices adoption on farmers' maize yield and net returns and predict the types of farm households most likely to benefit during scaling-up.

The empirical approach of this study relies on the use of the marginal treatment effect (MTE) approach applied in most studies (e.g. Abdul Mumin and Abdulai, 2021; Shahzad and Abdulai, 2021) in assessing the heterogeneous treatment effects of agricultural technology adoption on crop yields and net income. However, previous studies relied on the conditional MTE approach that has several limitations: (i) it restricts the evaluation of different expansionary policy effects among marginal entrants and (ii) it relies strongly on the variation of treatment effect across unobserved factors (Zhou and Xie, 2018, 2019).

As part of our contribution to the literature, we adopt the unconditional or the redefined MTE method proposed by Zhou and Xie (2018, 2019) that addresses the challenges of the conditional MTE. Using the redefined MTE approach, we show that both farmers' resource endowment and unobserved factors influence the marginal benefits of adopting agricultural technologies and practices. We also examine the heterogeneous effects of agricultural technology adoption on crop yields and net returns and predict the marginal farm household entrants most likely to benefit from adoption. To the best of our knowledge, this is the first study to explore such effects. Overall, our main result indicates that to enhance the adoption of SI practices during scale-up would require targeting farm households least likely to adopt based on observed socioeconomic characteristics.

The remainder of the study is organised as follows. Section 2 briefly discusses the study context. Sections 3 presents the conceptual model and the empirical strategy. Section 4 reports the empirical results, and Section 5 discusses the conclusions and policy implications.

2. Study context

2.1. Background

The Africa RISING[1] programme was initiated in 2012 across northern Ghana with the goal of lifting farmers out of hunger and poverty via sustainably intensified farming systems. The programme trained households on how to enhance their cereal-legume cropping systems via demonstration and dissemination of SI practices.[2] The SI practices were demonstrated to farmers through technology parks, which serve as learning and dissemination centres placed in all

1 Africa-RISING denotes Africa Research in Sustainable Intensification for the Next Generation.

2 https://africa-rising.net/.

intervention communities. Examples of the SI practices demonstrated included efficient fertilizer application, use of improved seed varieties, proper crop spacing and line sowing. These SI practices were expected to be adopted as a package to improving maize and legume yields. The programme also supported some farmers with inputs (e.g. improved seed) to test the SI practices on their fields.

Prior to the start of the programme, the administrative districts of the former three northern regions were stratified into six main domains based on agro-ecological potentials of the regions.[3] Fifty communities were sampled across the six domains: 25 communities were purposely sampled for treatment and received intervention from the programme, whereas the remaining randomly sampled 25 communities did not receive any intervention (Tinonin *et al.*, 2016), therefore classified as non-intervention communities. In 2015, the programme stopped its activity in 13 intervention communities due to lack of funds. Thus, in this study, we consider SI practices adopters as farmers who have adopted or applied SI practices on their plots for more than one cropping season after 2015. This is to capture the intensity of the application of SI practices by farmers in both the continuously engaged as well as dropped-out communities.

2.2. Data

The current study is a follow-up of the Ghana Africa-RISING Baseline Survey conducted in 2014 where 1,284 farm households across the intervention and controlled communities were sampled and interviewed (Tinonin *et al.*, 2016). We conducted a follow-up study in 2019 within the same period as in the baseline survey and followed the same sampling approach. Due to limited funds, we adopted a three-step approach in sampling our farm households. First, we conducted a power analysis to estimate the total sampled size required for the study.[4] Second, we proportionally adjusted the sample size to match the baseline sample of the regions and the communities. Third, we employed a random sampling approach to select the farmers from the list of the interviewed farmers across the 50 communities during the baseline survey. Overall, based on the power analysis, we sampled 429 farm households (212 households from continued communities and 217 households from dropped-out communities) and 271 farm households from the controlled communities. Using the same baseline questionnaire, a team of trained research assistants conducted face-to-face interviews with the sampled households across the regions. Information elicited from the farmers ranged from socioeconomic characteristics of the farm household, crop production to food and nutrition security.

3 The regions have been sub-divided into five regions as of now.

4 We used G*Power 3.1.9. version for the statistical power analysis. Our sample size corresponds to the power of 0.80, at alpha level 0.05, and with effect size of 0.20. This led to a sample size of 652. However, we increase the sample size to 700 in order to address issues such as attrition and non-responses.

2.3. Variables used

The variables used are factors identified to affect farmers' adoption of SI practices in the northern Ghana (Bellon *et al.*, 2020; Kotu *et al.*, 2017). This includes characteristics of the household head, such as gender, age, education attainment, dependency ratio, household size, farm size, number of livestock, group membership, access to extension services, number of productive assets, off-farm income, the time taken reach the nearest market or motorable road and agro-ecological zones. We expect the latter variable to proxy for long-term rainfall and temperature patterns, as well as the farming systems across the agro-ecological zones. For example, most farmers in the Sudan savannah zone plant on ridges due to the low soil depth compared with those in the Guinea savannah zone, where most farmers plant on the soil surface. In addition, mean annual rainfall for the Guinea savannah (1,100 mm) is higher than that of the Sudan savannah zone (900–1,000 mm) (MoFA, 2017).

Furthermore, we selected our outcome variables based on the programme's goals. We focused on maize yield and net returns on maize and legume yield. The maize yield is estimated as the total number of harvested grains in kilogram per hectare (kg/ha), whereas the net return is estimated as the amount of harvested maize and legume yields multiplied by the average village price less the cost of production (including family labour) in Ghana Cedis per hectare (GHS/ha).

Table 1 displays summary statistics of our sample household characteristics and the description of variables used. The table indicates that most of the farm households' heads are males, and the average age of a given household head is around 48 years. About 85 per cent of household heads cannot read and write, and most farmers source their agricultural information from extension agents or NGOs. The table also indicates an average maize yield of about 961 kg/ha in 2013 compared to around 1,081 kg/ha in 2018. In addition, the average net returns of maize and legume is about 367 GHS/ha in 2013 compared to around 826 GHS/ha in 2018. Finally, we find significant differences between the characteristics of SI practices adopters versus non-adopters (Table A1).

3. Conceptual framework and empirical strategy

Following Abdulai and Huffman (2014), we assume that farmers are risk neutral and will adopt the SI practices if the associated net benefits are greater than those from alternative practices. That is, suppose Y_1 represents the returns from SI practices adoption and Y_0 the returns from non-adoption, then farmers will adopt the SI practices if $Y_1 > Y_0$ (Pitt, 1983).

3.1. Estimation strategy

3.1.1. Overview of the traditional MTE framework

Following Heckman and Vytlacil (2005), we consider two potential outcomes Y_1 and Y_0, with a binary treatment indicator D, and pre-treatment

Table 1. Descriptive statistics

Variable	Description of variable	Mean	SD
Female	Gender of household head (1 = female, 0 = otherwise)	0.289	0.420
Age	Age of household head in years	47.520	14.032
Dependency ratio	Ratio of children under 15 and elders above 65 divided by household members between 15 and 64	1.103	0.711
Household size	Total number of household members	8.824	4.892
Read and write	Household head can read and write (1 = yes, 0 = otherwise)	0.154	0.361
Group	Farmer belong to a CBO or an FBO (1 = yes, 0 = otherwise)	0.163	0.387
Extension agent	Received advise from an extension agent (1 = yes, 0 = otherwise)	0.610	0.480
Farm size	Total crop area in hectares	1.44	1.590
Friends	Information from friends (1 = yes, 0 = otherwise)	0.142	0.350
Other farmers	information from other farmers (1 = yes, 0 = otherwise)	0.090	0.286
Herd size	Total livestock in tropical livestock units	3.395	6.658
Off-farm income	Off-farm income in Ghana Cedis (GHS)	135.400	265.893
Productive assets	Total number of durable assets	8.275	6.366
Market	Minutes taken to reach the nearest weekly market	31.76	25.543
Motorable road	Minutes taken to reach the nearest motorable road	6.180	11.041
Guinea savannah	Farmer lives in Guinea savannah zone (1 = yes, 0 = otherwise)	0.847	0.361
Sudan savannah	Farmer lives in Sudan savannah zone (1 = yes, 0 = otherwise)	0.153	0.360
Maize yield 2013	Harvested maize yield in kg/ha in 2013	961.00	688.739
Net returns 2013	Value of maize and legume output in GHS/ha	366.500	2084.710
Outcome variable			
Maize yield 2018	Harvested maize yield in Kg/ha	1080.500	693.506
Net returns 2018	Value of maize and legume output in GHS/ha	826.000	2862.045
Observations		669	

Notes: SD represents standard deviation. FBO and CBO denote farmer-based organisation and community-based organisation, respectively. Sample size reduced to 669 households after removing missing responses.

covariates X, where Y_1 is the potential outcome if a farmer adopts $(D = 1)$ and Y_0 if does not adopt $(D = 0)$. The outcome equations can be expressed as:

$$Y_0 = \mu_O(X) + \varepsilon \tag{1}$$

$$Y_1 = \mu_1(X) + \varepsilon + \rho, \tag{2}$$

where $\mu_0(X)$ and $\mu_1(X)$ are the conditional means for non-adopters and adopters, respectively. ε is the error term, which includes all unobserved factors that influence Y_0, and ρ is the error term that includes all unobserved factors that influence the treatment effect $(Y_1 - Y_0)$. The equation of outcome Y, can be stated as:

$$\begin{aligned} Y &= (1-D)\,Y_O + DY_1 \\ &= \mu_0(X) + (\mu_1(X) - \mu_0(X))D + \varepsilon + \rho D. \end{aligned} \tag{3}$$

Assuming that the treatment effect model is represented by an index I_D, depends on the observed factors Z and the unobserved factors V, then the latent index can be expressed as:

$$I_D = \mu_D(Z) - V \tag{4}$$

$$D = \mathbb{I}(I_D > 0) \tag{5}$$

where $\mu_D(Z)$ is an unknown function, V is a latent random variable that captures unobserved factors, Z denotes a vector that captures the pre-treatment covariates X and includes instrumental variables that influence the treatment D.

The key assumptions underlying the latent index model are (i) ε, ρ and V are independent of Z given X, and (ii) $\mu_D(Z)$ is a non-trivial function of Z given X. Given the assumptions, treatment assignment can be written as:

$$\begin{aligned} D &= \mathbb{I}(F_{V|X}(\mu_D(Z)) - F_{V|X}(V) > 0) \\ &= \mathbb{I}(P(Z) - U > 0), \end{aligned} \tag{6}$$

where $F_{V|X}(.)$ denotes the cumulative distribution V given X, and $P(Z)$ denotes the propensity score given Z. $U = F_{V|X}(V)$ represents the quantiles of V given X, and it follows the standard uniform distribution. It can be observed from Equation (6) that the Z affects the treatment status via the propensity score $P(Z)$.

Heckman and Vytlacil (2005) defined the MTE as a function of the pre-treatment covariates $X = x$ and the normalised latent variable $U = u$. That is, formally:

$$\begin{aligned} MTE(x,u) &= \mathbb{E}[Y_1 - Y_0 | X = x, U = u] \\ &= \mathbb{E}[\mu_1(X) - \mu_0(X) + \mathbb{E}[\rho | X = x, U = u] \end{aligned} \tag{7}$$

Causal estimands such as the average treatment effect (ATE), the treatment effect on treated (TT) and the treatment effect on the untreated (TUT) can be expressed as weighted averages of the $MTE(x,u)$.

3.1.2. The newly defined MTE framework

Zhou and Xie (2018, 2019) argued that, under the generalised Roy model, U captures all the unobserved factors that affect both the treatment status and treatment effect heterogeneity. They also argued that the latent index structure suggests that the entire treatment effect heterogeneity that is important for selection bias can be expressed as a function of (i) the propensity score $P(Z)$ and (ii) the latent variable or resistance to adopt U. This means that a person is treated only if her propensity score exceeds her latent resistance to adopt. Given $P(Z)$ and U, the treatment effect status D is fixed and independent of the treatment effect. This condition mirrors the expression of Rosenbaum and Rubin (1983) result on propensity score, but with an extra condition U in this case:

$$Y_1 - Y_0 \perp D | P(Z), U, \tag{8}$$

where $\perp$ denotes independency. Zhou and Xie (2018, 2019) redefined the *MTE* as the treatment effect based on the propensity score ($P(Z)$) (and not on the vector of covariates X) and the latent resistance to treatment (U or u):

$$\widetilde{MTE}(p,u) \triangleq \mathbb{E}\left[Y_1 - Y_0 | P(Z) = p, U = u\right] \tag{9}$$

The advantages of the redefined $\widetilde{MTE}(p,u)$ over the old $MTE(x,u)$ are: (i) it is simply a bivariate function that captures treatment effect heterogeneity in a more parsimonious way, (ii) it is very easy to be visualised and (iii) it can be used to predict different policy changes or policy treatment effects compared to the old $MTE(x,u)$ (Zhou and Xie, 2018, 2019). Furthermore, just as the traditional $MTE(x,u)$, causal estimands such as the ATE(p), TT(p) and TUT(p) can be estimated using appropriate weights from the propensity score (Zhou and Xie, 2018, 2019).

3.1.3. Overview of the traditional marginal policy relevant treatment effect

To predict the policy implications of a programme expansion, Heckman and Vytlacil (2005) proposed the policy relevant treatment effect (*PRTE*) concept, defined as the average effect of changing from a baseline policy to an alternative policy shift into treatment. That is

$$PRTE \triangleq \frac{\mathbb{E}(Y|\text{Alternative Policy}) - \mathbb{E}(Y|\text{Baseline Policy})}{\mathbb{E}(W|\text{Alternative Policy}) - \mathbb{E}(W|\text{Baseline Policy})} \tag{10}$$

where W is the treatment choice taken after a policy change. Heckman and Vytlacil (2005) showed that conditional on $X = x$, the *PRTE* is the weighted averages of the $MTE(x,u)$. Given the importance of marginal policy changes in affecting economic outcomes of interest, Carneiro, Heckman and Vytlacil (2010) proposed the marginal policy relevant treatment effect

($MPRTE$) concept as the directional limit of the $PRTE$. The $MPRTE$ is estimated under the assumption that the policy change occurs via a shift in the conditional distribution of $P(Z)$ given X.

3.1.4. The redefined marginal policy relevant treatment effect

Following the same argument by Carneiro, Heckman and Vytlacil (2010), Zhou and Xie (2018, 2019) proposed a policy change that shifts the conditional distribution of the $P(Z)$ directly without conditioning it on X. This strategy captures policy changes that incorporate individual treatment effect heterogeneity via the values of $P(Z)$, which could be induced by the differences in baseline characteristics X or the instrumental variables $Z|X$. Zhou and Xie (2018, 2019) considered a class of policy changes indexed by a scalar value α. Given $P(Z) = p$, they defined the $MPRTE$ as the limit of the $PRTE(p, \alpha\lambda(p))$ as α approaches zero the following way:

$$\begin{aligned}\widetilde{MPRTE}(p) &= \lim\nolimits_{\alpha\to 0} PRTE(p, \alpha\lambda(p)) \\ &= [Y_1 - Y_0 | p(Z) = p, U = p] \\ &= \widetilde{MTE}(p,p)\,. \end{aligned} \tag{11}$$

where λ is a real scalar function. Their proposed equation above also shows that at each level of propensity score, $\widetilde{MPRTE}(p)$ equals $\widetilde{MTE}(p,p)$ at the margin where $p = u$.

3.1.5. Treatment effect heterogeneity at the margin of adoption

The key question policymakers are interested in answering is how does technology adoption vary with farmers' resource endowment at the margin of adoption. To answer this question, we examine the components of Equation (12) after substituting equation (7) into equation (11).

$$\widetilde{MPRTE}(p) = \mathbb{E}\left[\mu_1(X) - \mu_O(X)\,|P(Z) = p\right] + \mathbb{E}\left[\rho|U = p\right]. \tag{12}$$

We note that the first component of Equation (12) captures treatment effect heterogeneity by the propensity score p, and the second reflects the treatment effect heterogeneity by the latent resistance to adopt U. Since at the margin of adoption $p = u$, the two components fall in the same dimension and thus the $p = P(Z)$ captures both treatment effects heterogeneity in observed and unobserved directions (Zhou and Xie, 2018, 2019). The adoption literature has focused extensively on the second component, which indicates that farmers who are more likely to benefit from new technologies are those most likely to adopt. However, the literature has paid less attention to the first component, which refers to the level of benefits from scaling up new agricultural technology. An observation of the first component shows that households who by observed socioeconomic characteristics appear least likely to adopt would benefit more from adoption (Zhou and Xie, 2018, 2019).[5]

5 See supplementary material (Appendix A3) for detailed exposition of this paradox.

Overall, the MTE framework is composed of the choice and return equations. The choice equation is estimated using a probit model, whereas the outcome equation is estimated using both the partial linear regression of Robinson (1988) and the local quadratic regressions of Fan and Gijbels (1996). Finally, given that the estimation of the redefined $\widetilde{MTE}$ requires selection instruments just as in the traditional MTE for identification, we follow Di Falco, Veronesi and Yesuf (2011) by using information sources as selection instruments (e.g. extension system, NGOs, friends and group membership). For an instrument to be valid, we expect that the information sources would influence the decision to adopt but not the output for non-adopters. We conduct a simple falsification test to check the validity of the instruments. We find that the instruments are valid and relevant (Table A2).

4. Empirical results

4.1. Decision to adopt SI practices

The first stage of the $\widetilde{MTE}(p,u)$ model estimates the propensity to adopt SI practices. Figure 1 displays the region of common support between adopters and non-adopters using the estimated propensity score from the first stage. The figure indicates a good region of common support between the adopters and non-adopters.

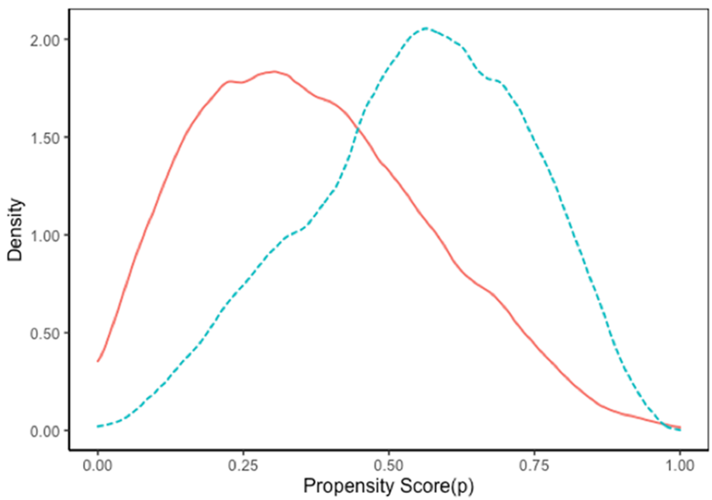

Fig. 1. Region of intersection or common support by adoption status. Dashed and solid lines denote adopters and non-adopters, respectively. Note that the propensity score is estimated from the choice equation or the first stage of the $\widetilde{MTE}$. The covariates for the choice equation for maize yield and net returns of maize and legume yield are the same.

Table 2. Decision to adopt SI practices (first stage of $\widetilde{MTE}$)

Variable	Average marginal effect
Female	0.057 (0.050)
Age	−0.001 (0.002)
Dependency ratio	−0.040 (0.030)
Household size	0.015*** (0.005)
Read and write	0.019 (0.058)
Group membership	0.101* (0.061)
Extension agent or NGO (Africa-RISING)	0.234*** (0.042)
Farm size, log	−0.812*** (0.112)
Friends	0.087 (0.067)
Other farmers	−0.142** (0.068)
Herd size	−0.003 (0.003)
Off-farm income, log	−0.018 (0.022)
Productive assets, log	0.165** (0.071)
Market, log	−0.010 (0.047)
Motorable road, log	0.040 (0.049)
Sudan savannah	0.007 (0.064)
Observations	669

Notes: *, ** and *** denote statistical significance at 10, 5 and 1 per cent levels, respectively. Note that the covariates for the choice equations for the first stage of the $\widetilde{MTE}$ are similar for maize yield and net returns of maize and legume yield, respectively.

Table 2 presents the average marginal effect of the decision to adopt the SI practices. The table suggests that group membership and information from extension agent or NGO increase farmers' propensity to adopt the SI practices by about 10 and 23 percentage points, respectively, while information from other farmers decrease the propensity to adopt by 14 percentage points. The former findings suggest that farmers' access to information and group membership can facilitate the easy adoption of SI practices. However, the latter finding may be attributed to the knowledge-intensive nature of the SI practices, linked to the difficulty of farmers to explain SI practices adequately to other farmers.

The results further indicate that households with more members are 2 percentage points more likely to adopt the SI practices, while those who own more productive assets are 17 percentage points more likely to adopt. These findings indicate that farmers need to have enough labour and resources to be able adopt the SI practices. Finally, the table reveals that farm households with large plot sizes are less likely to adopt by about 81 percentage points more. This result may be attributed to the high amount of labour that would be needed to implement the SI practices on such plots. This finding is not surprising because most farmers across the regions rely on family labour and depend on simple implements (e.g. cutlass).

4.2. Heterogeneity in treatment effects

Figures 2 and 3 illustrate the treatment effect heterogeneity based on the $\widetilde{MTE}(p,u)$ and the $MPRTE(p)$ among adopters and farmers at the margin of adoption, respectively, for maize yield and net returns per hectare, where propensity score p and latent resistance to adopt U range from 0 to 1. The shaded regions indicate the treatment effect heterogeneity—where the darker the shade the higher the treatment effect—along 10 deciles for each indicator, leading to 100 cells. The grid provides a powerful representation of the treatment effects for the treated (TT) and treatment effect on the untreated (TUT).

Figures 2 and 3 (left panels) show that the MTE declines with increases in U at each level of p, suggesting the presence of unobserved sorting on gain or self-selection. That is, farm households adopted the SI practices based on their idiosyncratic gains. Conversely, the figures indicate that at each level of U, p increases with increases in the MTE, indicating that high resource-endowed farm households who also adopted the SI practices derived higher returns. These results are consistent with other studies in agricultural technology adoption (e.g. Shahzad and Abdulai, 2021; Abdul Mumin and Abdulai, 2021).

In contrast with Figures 2 and 3 (left panels), Figures 2 and 3 (right panels) plot the treatment effects heterogeneity for the farm households at the margin of adoption, where $p = u$. The figures indicate that among the farm households at the margin of adoption, the MTE decreases with p, suggesting that farm households who by observed characteristics appear least likely to adopt would

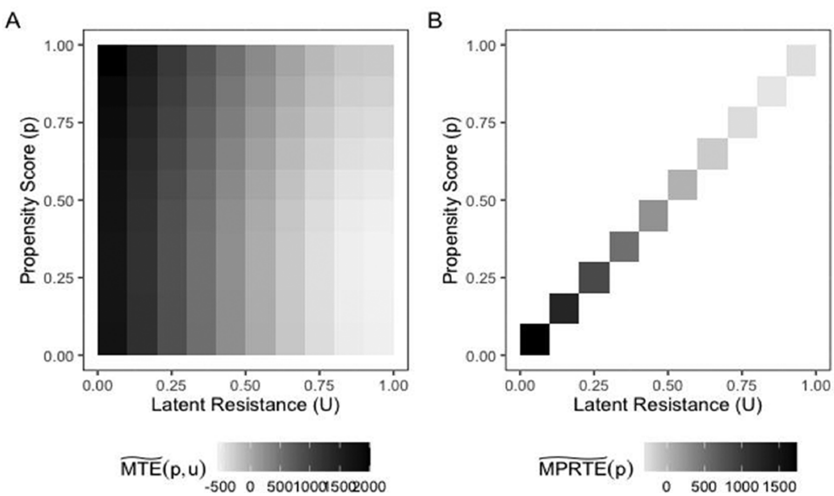

Fig. 2. Treatment effect heterogeneity based on $\widetilde{MTE}(p,u)$ and $MPRTE(p)$ for maize yield (kg/ha). Note that the darker the colour the higher the treatment effect.

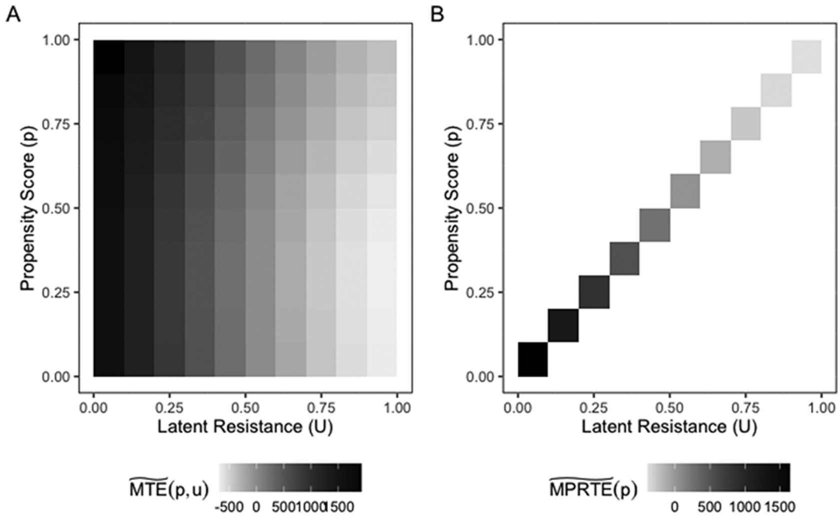

Fig. 3. Treatment effect heterogeneity based on $\widetilde{MTE}(p,u)$ and $MPRTE(p)$ for net returns of maize and legume yield (GHS/ha). Note that the darker the colour the higher the treatment effect.

Table 3. Estimated mean impacts of adopting SI practices

	Maize yield (Kg/ha)	Net returns of maize and legume yield (GHS/ha)
Parameter	(1)	(2)
ATE	285.460 (312.018)	1906.905* (1215.914)
TT	961.320** (456.968)	3138.313** (1818.570)
TUT	−258.339 (539.176)	910.919 (1958.646)
Observations	669	

Notes: Non-parametric bootstrap standard errors in parentheses (500 replications). ***, **, * significance at 1, 5 and 10 per cent levels, respectively. 1 USD = GHS 5.4. Estimates were based on $\widetilde{MTE}(p,u)$. Table A3 reports the estimated net returns of maize yield only.

benefit more. This paradox of negative selection is due to the unobserved sorting on gain[6], which is a novel finding of our analysis.

4.3. Impacts of SI practices adoption

Table 3 reports the ATE, treatment effect on the treated (TT) and treatment effect on the untreated (TUT) of adopting SI practices on maize yield and net returns per hectare, respectively. Overall, Table 3 suggests that TT > ATE > TUT, indicating that SI practices adopters benefited more than

6 We have also provided a graphical explanation of this result in supplementary material (Appendix A3).

non-adopters. This trend is further confirmed by the pattern in Figure A3, which explores the relationship between the causal estimands and p.

More specifically, Table 3 shows that the average maize yield and net returns per hectare for a randomly selected farmer are around 285 kg/ha and 1,907 GHS/ha, respectively. These figures lie between the benefits for the average farmer who adopts (maize yield: 961 Kg/ha; maize and legume yield: 3,138 GHS/ha), and the loss or foregone benefits for the average farmer who never adopted (maize yield only: −258 Kg/ha; maize and legume yield: 911 GHS/ha)[7]. We find a similar pattern for the average net returns of maize yield only (Supplementary Table A3).

4.4. Scaling-up policy effects among marginal farm household entrants

Since the ATE, the TT and the TUT rarely contribute to scaling-up policy issues (Heckman and Vytlacil, 2005; Mogstad and Torgovitsky, 2018), we estimate the marginal benefits of scaling up the training of farmers on how SI practices are implemented and the provision of support (e.g. enhancement of farm households' access to improved seed varieties) on maize yield and net income of maize and legume of farm households at the margin of adoption.[8] We estimate the marginal benefits of scaling up the programme using the linear instrumental variable method (IV) and the redefined $\widetilde{MPRTE}$ approach. For the IV method, we follow Carneiro, Heckman and Vytlacil (2011) by using the estimated propensity scores from the first stage of the $\widetilde{MTE}(p,u)$ as an instrumental variable in estimating the model. We note that the estimator in this case estimates the ATE for compliers (Angrist and Imbens, 1995; Carneiro, Heckman and Vytlacil, 2010).

Given that the estimated propensity score at the margin of adoption can be viewed as a proxy of households willingness to pay (adopt) or levels of resource-endowed households (Carneiro, Heckman and Vytlacil, 2011; Zhou and Xie, 2018, 2019), we estimate the marginal benefits associated with boosting or supporting different levels of resource-endowed households. That is, we estimate the marginal benefits associated with (i) supporting every marginal farm household entrants (a); (ii) supporting farm households who by observed socioeconomic characteristics appear more likely to adopt (b); (iii) focusing on farm households who by observed socioeconomic characteristics appear less likely to adopt (c) and (iv) targeting farm households who by observed socioeconomic characteristics have about 20 per cent chance of adopting SI practices (d).

Table 4 presents the scaling-up policy effects of the SI practices on farm households at the margin of adoption. The linear IV estimates indicate that the average benefits of adopting the SI practices due to a change induced by

7 We note that the positive net returns may be due to benefits from the legume yield.

8 This could be a policy initiative by the programme given the associated benefits of adopting SI practices. The overall aim here is to boost different farm households' probability to adopt the SI practices.

Table 4. Estimated benefits of scaling-up SI practices

Parameter	Policy	Maize yield (Kg/ha) (1)	Net returns of maize and legume yield (GHS/ha) (2)
$\widetilde{MPRTE}(p)$			
α	A	355.4045 (245.453)	1922.525** (967.560)
αp	B	89.448 (283.979)	1324.428 (1012.257)
$\alpha(1-p)$	C	570.494** (275.416)	2406.229** (1141.315)
$\alpha \mathrm{I}(p < 0.20)$	D	1430.980** (578.901)	4564.478** (2321.631)
Linear IV (used $P(Z)$ as instrument)		353.420 (221.600)	1420.170 (874.043)
Observations		669	

Notes: Non-parametric bootstrapped standard errors in parentheses (500 replications). ***, **, * significance at 1, 5 and 10 per cent levels, respectively. The $\widetilde{MPRTE}(p)$ was estimated using the robust semiparametric approach. 1 USD = GHS 5.4. We used the estimated propensity score from the first stage of the $\widetilde{MTE}(p,u)$ as an instrumental variable for the linear IV estimation.

the local instrument (or propensity score) would lead to positive and insignificant effects on maize yield and net returns of maize and legume yield among compliers or adopters.

However, for the $MPRTE(p)$, Table 4 suggests that the third (C) and last (D) scaling-up policies would lead to the highest benefits, while the second policy (B) would lead to the lowest benefits. We also find similar pattern for the net returns of maize yield only (Table A3). Table 4 further suggests that the average marginal benefits for farmers at the margin of adoption (the first policy (A)) are lower than the average benefits for adopters (TT). This result implies the need for policymakers to be cautious when using average estimates for scaling up policy decision.

4.5. Which farm households will benefit most from the four scaling-up policy changes?

To identity the farm households who by observed characteristics would benefit most from the four scaling-up policy changes at the margin of adoption based on the $MPRTE(p)$, we examine the relationship between the treatment effect, the propensity score p and the latent resistance to adopt U under the four policy changes for maize yield and net returns of maize and legume yield, respectively.

Figures 4 and 5 suggest that under the four policy changes, farm households located at the lower end of the propensity score (low resource-endowed farm households) would derive the highest benefits when the SI practices are scaled up, indicating that scaling-up policy targeted towards these farm households would lead to the highest marginal benefits. The figure also indicates heterogeneity in treatment effects, reinforcing the need to target SI practices during

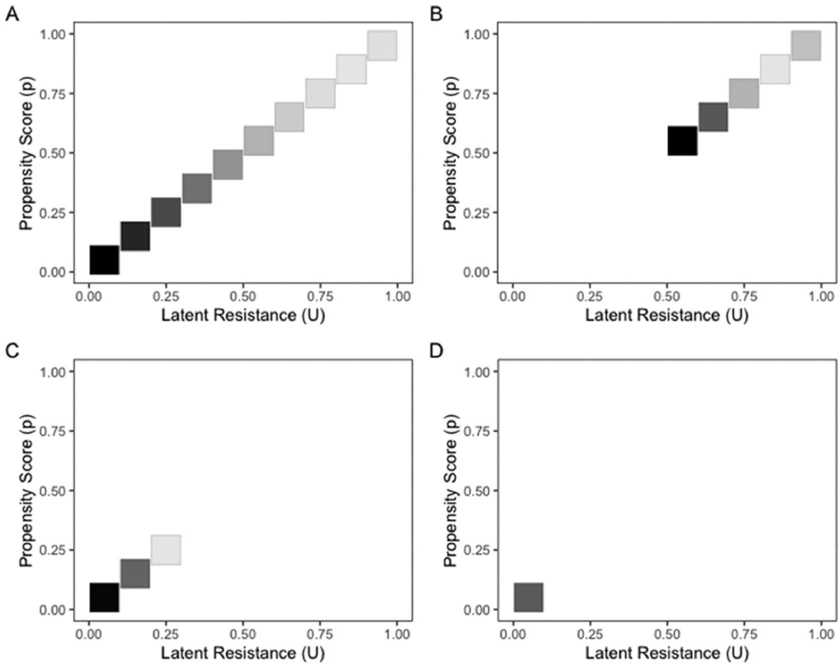

Fig. 4. Scaling-up SI practices under four policy changes for maize yield (Kg/ha) based on $MPRTE(p)$. Policy A favours all farmers (top left), Policy B favours more resource-endowed farmers (top right), Policy C favours less resource-endowed farmers (bottom left) and Policy D favours farm households who have 20 per cent chance of adopting the SI practices (bottom right). The darker the colour, the higher the treatment effects.

scaling-up. Finally, several sensitivity tests reveal our estimates to be robust to different model specifications (supplementary material).

5. Conclusions and policy implications

This paper examines the marginal and the average benefits of adopting sustainable agricultural intensification practices on farmer maize yield, net returns per hectare of maize and legume planted and also predicted the marginal farm household entrants that will benefit the most during scale-up, using the newly redefined MTE framework approach.

Our findings suggest that the adoption of SI practices is driven by access to information, group membership, household size and the number of productive assets owned by the household. They also show that both farmers' unobserved characteristics and resource endowment differentially affect the marginal and average benefits of SI practices adoption. Point estimates revealed that the adoption of SI practices increased farmers' maize yield and net returns per hectare. The novel finding of our analysis points to all potential policy options in scaling-up SI practices as disproportionately

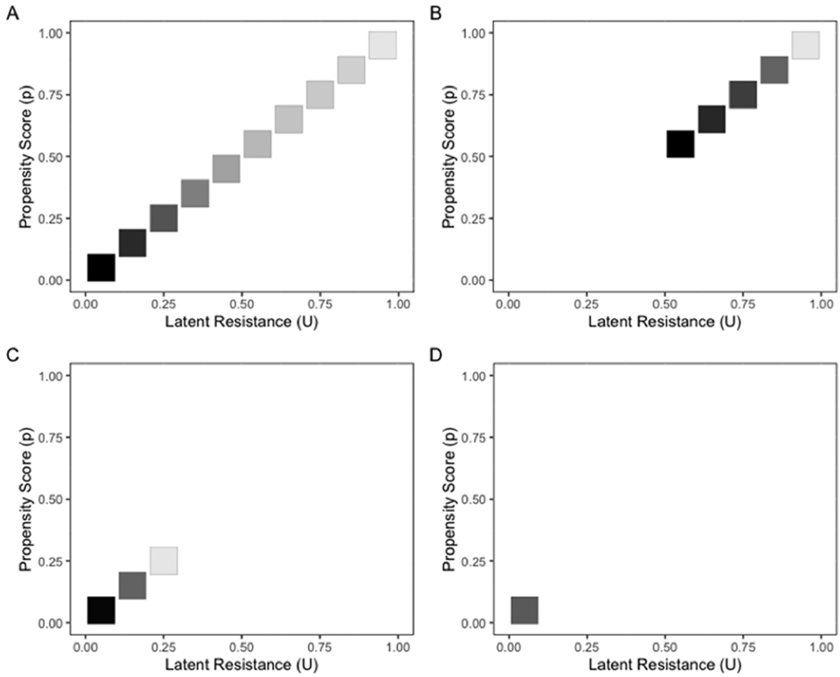

Fig. 5. Scaling-up SI practices under four policy changes for net returns of maize and legume yield (GHS/ha) based on $MPRTE(p)$. Policy A favours all farmers (top left), Policy B favours more resource-endowed farmers (top right), Policy C favours less resource-endowed farmers (bottom left) and Policy D favours farm households who have 20 per cent chance of adopting the SI practices (bottom right). The darker the colour, the higher the treatment effects.

favouring farm households least likely to adopt based on their observed characteristics.

On the policy side, our findings suggest that policies and programmes directed towards improving crop productivity and farm income among poor rural farm households can be achieved through wide diffusion of SI practices. Despite the heterogeneity of farming systems in northern Ghana, in turn implying heterogeneity in policy effects during scaling-up, our findings indicate the need for policymakers to be cautious in using average estimated benefits based on on-station trials or small-scale pilot agricultural interventions for programme expansion. Indeed, the use of such estimates to benchmark the scaling-up of new agricultural technologies could explain the difference between actual performance and on-station or pilot estimates. Finally, our results suggest that the diffusion of SI practices alone should be supported by enabling policy helping sustained and time-consistent adoption. These elements are crucial to avoid dis-adoption of improved agricultural technologies that seems common in sub-Saharan Africa (SSA) agriculture nowadays. Provision of support services such as strengthening agricultural extension programmes, facilitating farmers' interaction and knowledge exchange through cooperative groups and boosting small-scale mechanisation of agricultural time-intensive operations (e.g. land preparation, planting and harvesting) can help enhance successful and consistent adoption. These policies would require a strong commitment of policymakers in collaborating with the private business mechanisation sector during the scaling-up process.

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Supplementary data

Supplementary data are available at *ERAE* online.

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