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Stimulating Innovations for Sustainable Agricultural Practices among Smallholder Farmers: Persistence of Intervention Matters

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ABSTRACT *As part of the dissemination of sustainable intensification (SI) of agricultural practices in northern Ghana, farmers were conditionally induced with inputs to adopt the SI practices. We study the effects of the conditional inducement on maize yield and net income of farmers under a quasi-randomised phase-out design. We examine the effects of the inducement by comparing continuous induced farmers with past induced and non-induced farmers. Our results indicate that the conditional inducement led to an increase in the maize yield and the net income of continuously induced farmers, on average. Estimates also suggest that the continuously induced farmers would have had their maize yields and net incomes decreased by about 64 per cent and 54 per cent, respectively if the inducement had been discontinued. Distributional analysis reveals that the inducement effects are heterogeneous and that past inducement impacted more on the maize yield and the net income of farmers at the lower quantiles. We conclude that appropriate conditional inducement can stimulate farmers' adoption. Besides, the duration of intervention matters and must not be overlooked in interventions that necessitate gaining experience and learning.*

KEYWORDS: adoption; inducement; sustainable intensification practices; northern Ghana; quasi-randomised phase-out design

1. Introduction

Incentivising farmers to adopt new agricultural technologies to improve crop productivity and net returns can be one of the ways to realise the United Nations development goal of ending hunger by 2030, especially in Sub-Saharan Africa (SSA). Governments, development agencies and research institutions have developed policies and disseminated agricultural technologies with the aim of helping smallholder farmers to increase their crop productivity and farm incomes. To stimulate as well as sustain adoption among smallholder farmers during the diffusion of agricultural technologies, development agencies and governments have provided inputs and have enhanced farmers' human capital through the provision of extension services (Maggio, Mastrorillo, & Sitko, 2021). However, several studies (for example, Arslan, Belotti, &

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Lipper, 2017; Grabowski, Kerr, Haggblade, & Kabwe, 2016; Neill & Lee, 2001) have shown dis-adoption of agricultural technologies and practices among smallholder farmers after the termination of most programmes.

Several reasons have been attributed to the low adoption rates, including lack of information (Ashraf, Giné, & Karlan, 2009), high transaction cost due to bad road network (Suri, 2011), lack of access to formal credit and insurance (Karlan, Osei, Osei-Akoto, & Udry, 2014), procrastination and inconsistencies in the use of inorganic fertilisers (Duflo, Kremer, & Robinson, 2011), lack of access to inputs (Emerick & Dar, 2021), and differences in agroecological conditions (Bouwman, Andersson, & Giller, 2021; Giller et al., 2011). Nevertheless, the dissemination methods used to spur farmers into adopting new agricultural technologies have received less attention in the adoption literature (Emerick & Dar, 2021).

Farmer field days[1] and mobile technology dominate current dissemination methods used in developing countries, particularly in SSA (Aker, 2011; Fafchamps & Minten, 2012; Cole & Fernando, 2016). However, recent studies in Malawi and Kenya have shown that farmer field days are less effective in encouraging farmers into adopting new agricultural technologies and practices (Fabregas, Kremer, Robinson, & Schilbach, 2017; Maertens, Michelson, & Nourani, 2021). Besides, the use of mobile technology in diffusing new technologies in SSA is still in its nascent stage (von Braun, 2018).

In this paper, as part of the dissemination of sustainable intensification of agricultural practices (SI practices)[2] in northern Ghana, we examine the effects of conditional inducement on maize yield and net income of farmers. In our evaluation of the conditional inducement effects, we deviate from the conventional approach due to the unique nature of the study design.[3] For instance, compare to previous studies such as Duflo et al. (2011) who contrasted treated and control farm households to estimate the effect of inducing farmers to adopt chemical fertilisers, we on the other hand compare treated farm households with untreated and counterfactual households for whom intervention was implemented but later discontinued.

We situate our study within the context of an agricultural programme in northern Ghana, where the farming systems are heterogeneous just as in other regions in SSA (Giller et al., 2011; Kamau, Stellmacher, Biber-Freudenberger, & Borgemeister, 2018; Kuivanen et al., 2016). In addition, the regions in northern Ghana are characterised by a high rate of poverty among most farm households (Cooke, Hague, & McKay, 2016; MoFA, 2017). The present study is based on data collected as part of the Africa Research in Sustainable Intensification for the Next Generation (Africa-RISING)[4] programme in northern Ghana. The programme was established in selected communities with their corresponding control communities in 2012. However, in 2016 the programme phased-out some of the intervention communities due to inadequate funding from the major sponsor.

We exploit the changes in the project execution in addressing the objectives of the study by comparing farmers at different treatment levels (continued, phased-out, and control). Our comparisons provide answers to the ensuing policy-relevant questions: (a) does inducement of farmers stimulates adoption? (b) do effects from inducement vary across farm households? and (c) do effects decay at the same rate in the absence of inducement? These policy-relevant questions are not well addressed in the literature on technology adoption.

Overall, we contribute to small, but growing research on how to scale up and out agricultural technologies in SSA. For example, our comparison of continuous induced farmers with past induced farmers provides an answer to the question of how should agricultural programmes that involve learning and experimentation by farmers be terminated and when? The study also provides insights about which farm households are much more likely to lose out or gain from the termination of inducement, and what would have been the gains or losses among the continuously induced farmers if the inducement had been terminated at the same time with farmers in the phased-out communities.

Our results suggest that the inducement had a positive and significant effect on maize yield and net income of farmers in the continued communities. Point estimates indicate that the continuously induced farmers could have had their maize yields and net incomes decreased, on average, by about 64 per cent and 54 per cent respectively if the inducement had been discontinued. Distributional estimates reveal that the inducement effects on maize yield and net income of farmers are heterogeneous across the farm households, and that past inducement impacted more on maize yield and net income of farmers at the lower quantile distribution.

The next section of the paper describes the Africa-RISING programme, followed by the theoretical framework and methodology in Section 3. Sections 4 and 5 present the results and discussion, respectively, whereas section 6 concludes.

2. The Africa-RISING programme

Africa-RISING was launched in northern Ghana in 2012. The objective was to help move farmers out of hunger and poverty through sustainably intensified farming systems. Prior to the beginning of the programme in 2012, the programme stratified the districts in the northern regions of Ghana into six domains based on market access and agricultural potential of the regions (Guo & Azzarri, 2013). Fifty communities were sampled across the domains: 25 intervention communities were purposely sampled to receive interventions, whereas the rest, randomly sampled, were assigned to non-intervention communities (Guo & Azzarri, 2013; Tinonin et al., 2016). In addition, the programme ensured that the non-intervention communities did not share similar weekly markets with the intervention communities (Guo & Azzarri, 2013; Tinonin et al., 2016).

In the intervention communities, farmers were supported to improve their crop productivity through training, input support, and demonstration of SI practices. The SI practices were hosted in on-farm experimental sites (also known as technology parks) located in all the intervention communities and were demonstrated to all farmers in the communities. The SI practices demonstrated to the farmers included proper fertiliser application, different crop spacing, line sowing, use of improved seed varieties, and maize-legume intercropping.

To stimulate farmers' adoption, the programme incentivised some of the trained farmers to adopt the SI practices by offering the farmers improved seeds and fertilisers. The items were given out to the farmers on the condition that they replicate practices from the park. It is worth noting that the items were not randomly assigned. The programme also assisted the incentivised farmers to implement the SI practices on their individual farms. The programme achieved this through its collaboration with the government extension agents. Farmer field days were also organised within the intervention communities to expose other farmers to the SI practices. However, in 2016, the programme phased-out 13 intervention communities due to limited funding from the leading sponsor, and then proceeded to work with the rest of the 12 intervention communities.

3. Theoretical framework and methodology

3.1. Theoretical framework

Our theoretical framework is based on the model of learning about agricultural technology of Conley and Udry (2010). Here, we assume that farmers know the biophysical conditions of their surroundings (for example, soil type, rainfall pattern), but do not know the correct combination of inputs that would lead to the highest crop yield, which we expect farmers to learn from the technology park and other farmers. The use of information from the technology park, which involves the combination of inputs coupled with their related crop yields and profits, is expected to provide several information to farmers. In addition, a new set of knowledge will be generated as farmers continue to implement the new technologies. We expect that the new information would help reduce the level of uncertainties and incomplete knowledge of the inputs combination. We surmise that incentivising farmers with conditions would motivate the use of information from the technology park, thereby increasing the rate of adoption, which may further lead to increases in crop yield and net income of farmers. Finally, we expect farmers to continue to adopt the technologies provided the net returns are greater than the returns from other alternative practices (Abdulai & Huffman, 2014; Pitt, 1983).

3.2. Methodology

To identify the average effect of the inducement on maize yield and net income of farmers, we follow the potential outcome framework of the form:

$$Y = DY_1 + (1 - D)Y_0, \tag{1}$$

where Y is the real-valued outcome, Y_1 and Y_0 are the potential outcomes of a treated and a non-treated farmer, respectively, and D is a binary variable indicating whether a farmer is treated (1) or not (0). Under the assumption of selection on observables, Y can be estimated by conditioning on the observed covariates, X (for example, gender of household head, age, ability to read and write). To examine the policy implication of the intervention, we estimate the average treatment effect on the treated (ATT). The ATT estimates the average gains for the farmers who got induced in the continued and phased-out communities. We estimate the ATT under the assumption of selection on observables as:

$$\mathbb{E}[Y_1 - Y_0|D = 1] = \mathbb{E}[Y_1|D = 1] - \mathbb{E}[Y_0|D = 1]. \tag{2}$$

More specifically, under the assumption of selection on observables, we adopt the kernel matching (Caliendo & Kopeinig, 2008) and the inverse propensity score weighting (IPW) approach combined with a machine learning method (that is, the least absolute shrinkage and selection operator (Lasso)) to estimate the ATT. The IPW-Lasso is considered a doubly robust method because only one of the models needs to be specified correctly (Belloni, Chernozhukov, Fernández-Val, & Hansen, 2017; Imbens & Wooldridge, 2009). The Lasso regression selects the appropriate covariates for the estimation (Belloni, Chernozhukov, & Hansen, 2014).

Furthermore, since famers' decision to be induced could be affected by unobserved factors (for example, technical and managerial skills), we employ an instrumental variable regression method to estimate the ATT. We estimate the ATT under the assumption that the treatment effect and farmers' unobserved factors (for example, past experience, knowledge) are heterogeneous across the farm households. We adopt the marginal treatment effect (MTE) approach proposed by Mogstad and Torgovitsky (2018) to estimate the ATT. The estimator extrapolates effect from farmers influenced by an instrument to be induced to induced farmers not affected by an instrument (Mogstad & Torgovitsky, 2018).

3.3. Heterogeneous treatment effects

Although the average treatment effect is interesting in determining the effect of inducement on farmers' maize yields and net incomes, it fails to unravel the heterogeneous treatment effects of the inducement across the farm households. Moreover, policymakers may be more interested in knowing the effects of the conditional inducement on maize yield and net income of farmers at the tail end of the maize yield and net income distribution. Thus, we adopt the instrumental variable quantile treatment framework proposed by Chernozhukov and Hansen (2005) in exploring the heterogeneous treatment effects of inducement on maize yield and net income of farmers. We estimate the τ th quantiles of the outcomes under the treatment ($D = d$), conditional on $X = x$. That is, we estimate the quantile treatment effect of the form:

$$Y_d = q(D, X, U_d), \text{ where } U_d \sim U(0, 1), \tag{3}$$

where U_d denotes the unobserved random variable, and $q(D, X, U) = Q_{Y_d}(\tau|x)$ measures the conditional τ-quantile of Y_d. Since farmers' unobserved factors can affect the decision to be induced, we adopt the instrumental variable quantile regression (IVQR) via the control function method in estimating Y_d (Lee, 2007).

3.4. *Addressing potential endogeneity issues*

Since the conditional inducement was not randomly assigned in the intervention communities (continued and phased-out), we expect farmers in the intervention communities to self-select into programme. We follow Di Falco, Veronesi, and Yesuf (2011) by using information sources (for example, extension agent and group membership) as instruments in estimating: (i) the effects of the continuous inducement on maize yield and net income of induced farmers in the continued community, and (ii) the effects of past inducement on maize yield and net of income past induced farmers. We expect that farmers' access to information from extension services or groups (for example, farmer-based organisation) about the SI practices should influence farmers' decision to be induced. On the other hand, we do not expect the information sources to affect the outcome variables or the outcome variables of farmers in the non-intervention communities (Di Falco et al., 2011).

To also estimate the gains or losses associated with the continuous inducement, we follow other studies (for example, Abdulai, 2016; Bellon, Kotu, Azzarri, & Caracciolo, 2020; Kassie, Teklewold, Marenya, Jaleta, & Erenstein, 2015; Khonje, Manda, Mkandawire, Tufa, & Alene, 2018; Michler & Josephson, 2017) by using the time taken to reach the nearest weekly market or a motorable road to proxy farmers' ease and distance taken to reach the nearest market as instrumental variables. We expect that the closer and easier for farmers to interact with market forces would influence their decision to be induced.

On the other hand, we do not expect that the time taken to reach the nearest weekly market or a motorable road should directly affect the outcome variables. We follow Di Falco et al. (2011) by conducting a falsification test to check the validity of the excluded instruments. The test results showed that the information sources jointly affected farmers' decision to be induced, but not on the outcome variables (Tables A2 and A3). Also, the test results indicated that the time taken to reach the nearest weekly market or a motorable road jointly affected the decision to be induced and not directly on the outcome variables of non-induced farmers (Table A4).

3.5. *Cost effectiveness of the conditional inducement*

Although a full cost-benefit analysis of the inducement *vis-à-vis* a farmer field day is beyond the scope of this study, we conduct a back-of-the-envelope calculation of the cost effectiveness of inducement compare to the cost of a farmer field day organised in 2018 in a continued community. We estimate this using information from field officers across the three regions. A benefit-cost ratio greater than 1 is considered to generate a benefit for every Ghana cedis invested.

3.6. *Data*

The current study is a follow-up of the Ghana Africa-RISING Baseline Survey conducted in 2014 where 1248 farm households were surveyed across both the intervention and non-intervention communities (Tinonin et al. (2016). We conducted our follow-up study within the same period as in the baseline study. However, we adopted a three-step approach in sampling the households given the limited budget for the study.

First, a power analysis was conducted to establish the appropriate sample size for the follow-up study,[5] which led to a total sample size of 652 farmers, but we increased the sample size to 700 farmers to address attrition, even though we did not encountered any issues during the period of the data collection. Second, we adjusted the sample size of the regions and other administrative divisions to match the baseline information. Finally, we used a simple random sampling method to sample farm households from the list of households surveyed during the baseline study.

Based on the power analysis, we sampled 212 farmers from the continued communities, 217 households from the phased-out and 271 households from the non-intervention communities using our randomised list of sampled farmers from the baseline list. We note that the selected farmers from the continued and phased-out communities also included farmers who were not directly induced by the programme, but participated in the farmer field days organised in the intervention communities. That is, our sampled also included 40 and 48 farm households from the continued and phased-out communities, respectively. We used information from these households to estimate the cost effectiveness of inducement compare to a farmer field day.

Prior to the survey, enumerators were hired and trained for about 6 days. Under the guidance of the leading author, the enumerators conducted face-to-face interviews with the selected farmers. Farm households were interviewed on questions that covered from socioeconomic characteristics of the household, crop production to food and nutrition security.

3.7. Variables used and descriptive statistics

The covariates used are factors identified to influence farmers' adoption of SI practices (Bellon et al., 2020; Kim, Mason, Snapp, & Wu, 2019; Kotu, Alene, Manyong, Hoeschle-Zeledon, & Larbi, 2017). These include information about the household head (for example, gender, age, dependency ratio), dependency ratio), household size, farm size, extension services, group membership, herd size, off-farm income, number of productive assets owned by the household, and the time is taken to reach the nearest motorable road and weekly market. For the outcome variables, we focused on maize yield and net income since maize is the most cultivated and consumed crop across all the regions. We measured maize yield as the harvested grain yield in kilogram per hectare (kg/ha), while the net income was calculated by multiplying the average village price by the quantity harvested less the cost of production in Ghana cedis per hectare (GHS/ha).

Table A1 reports the descriptive statistics of our sampled farm households. The table suggests that the majority of the farm households are headed by men, and the average age of a given household head is about 48 years. The table also indicates that about 85 per cent of the households sourced their agricultural information from extension agents or NGOs. The average household size, livestock holdings and farm size of a given farm household are 9, 4 and 1.42, respectively. Finally, a household, on average, harvested about 1075 (kg/ha) of maize grains and derived a net income of about 809 GHS/ha. Table 1 also reports the mean and differences between the farm household characteristics by treatment type. The table suggests significant differences in the farm household characteristics, indicating that a simple mean difference between the outcome variables by treatment type cannot be attributed to the inducement effect, since the estimate will be biased.

4. Results

4.1. Determinants of the decision to be induced in continued and phased-out communities

Table 2 reports the average marginal effect of the decision to be induced in both continued and phased-out communities. The findings imply that access to extension services and the time

Table 1. Mean and differences in household characteristics by treatment type

Variable	Continued (1)	Phased-out (2)	Non-intervention (3)	Difference (1)–(2)	(1)–(3)	(2)–(3)
Female	0.390	0.350	0.085	0.040**	0.310*	0.270***
	(0.489)	(0.479)	(0.279)			
Age	48.341	47.357	47.296	0.984	1.045*	−0.603
	(14.028)	(14.142)	(13.976)			
Dependency ratio	1.097	1.043	1.134	0.054	−0.04***	−0.09***
	(0.751)	(0.556)	(0.786)			
Read and write	0.170	0.130	0.162	0.040	0.008	−0.003**
	(0.376)	(0.331)	(0.369)			
Household size	7.770	9.750	8.800	−1.98***	−1.030	0.950
	(3.824)	(5.251)	(5.270)			
Group	0.270	0.200	0.100	0.070**	0.170***	0.10***
	(0.444)	(0.404)	(0.300)			
Extension services	0.820	0.660	0.440	0.160**	0.380***	0.38***
	(0.388)	(0.476)	(0.497)			
Farm size	0.820	1.366	1.920	−0.546**	−1.10***	−0.554**
	(0.514)	(1.23)	(2.227)			
Livestock holdings	3.149	3.561	3.680	−0.412**	−0.530	−0.119
	(7.158)	(5.530)	(7.746)			
Off-farm income	124.911	152.313	148.890	−27.402	−23.978	3.423
	(242.441)	(247.248)	(362.453)			
Productive assets	8.000	9.000	8.000	−1.00***	0.000	1.000
	(5.179)	(5.856)	(7.259)			
Market	29.933	32.214	33.217	−2.281	−3.284	−1.003
	(20.569)	(24.913)	(28.766)			
Motorable road	6.067	5.085	6.849	0.982	−0.792	−1.764*
	(7.373)	(8.043)	(14.435)			
Northern	0.340	0.450	0.610	−0.110**	−0.270**	−0.160**
	(0.476)	(0.499)	(0.489)			
Upper East	0.390	0.090	0.070	0.300**	0.320**	0.020**
	(0.488)	(0.284)	(0.261)			
Upper West	0.270	0.460	0.320	−0.190**	−0.050	0.140*
	(0.444)	(0.499)	(0.466)			
Outcome variable						
Maize yield	1196.400	980.232	1059.832	216.17**	136.57**	−79.600
	(757.871)	(655.455)	(655.455)			
Net income	1426.067	1222.027	1281.030	204.04**	145.04**	−59.000
	(841.193)	(789.710)	(902.974)			
Observations	212	217	271			

Notes: Standard deviations in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ denote significant at 10 percent, 5 percent, and 1 percent, respectively. The Mann–Whitney test and the Chi-square test were used for the continuous and binary variables, respectively.

taken to reach the nearest weekly market increase farmers' propensity to be induced by 60 and 10 percentage points, respectively. These results indicate that farmers' easy access to both information and markets can motivate their decision to be induced. The table also shows that household size, age of household head (a proxy of experience), and the number of productive assets owned by a household increases the propensity to be induced by 1, 0.2 and 8 percentage points, respectively. These results suggest that farmers' resource endowment affects farmers' decision to be induced.

Furthermore, the results reveal that a unit increase in household dependency ratio and farm size would reduce the propensity of the farm household to get the inducement by 4 and 6 percentage points, respectively. These findings imply that farmers would require more labour in implementing the SI practices and thus may hinder their decision to be induced. Finally, our

Table 2. Determinants of the decision to be induced in both continued and phased-out communities

Variable	Average marginal effect
Female	0.042
	(0.041)
Age	0.002*
	(0.001)
Dependency ratio	−0.038**
	(0.019)
Read and write	−0.058
	(0.040)
Household size	0.013***
	(0.003)
Group	0.055
	(0.036)
Extension services	0.597***
	(0.040)
Farm size	−0.058***
	(0.040)
Livestock holdings	0.005
	(0.018)
Off-farm income	−0.044
	(0.031)
Productive assets	0.080*
	(0.047)
Market	0.098**
	(0.031)
Motorable road	−0.033
	(0.033)
Northern	−0.125**
	(0.034)
Upper East	−0.058
	(0.047)
Observations	612

Notes: Standard error in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ denote significant at 10 percent, 5 percent, and 1 percent, respectively.

result shows that a farmer who lives in the Northern Region is 12 percentage points less likely to be induced than a farmer in the Upper West Region. A plausible reason for this finding is that farmers in the Northern Region are more likely to engage in off-farm income activities due to their easy access to markets. Moreover, the poverty rate among households in the Upper West Region is higher than households in the Northern and Upper East Regions (Cooke et al., 2016).

4.2. Mean effect of conditional inducement

We first explore the unconditional effect of the inducement on maize yield and net income of farmers by using the kernel density curve. Figure 1 graphs the kernel density curves of maize yield and net income of farmers by treatment type. The figure indicates shifts in the curves of maize yield and net income of farmers in both the continued and phased-out communities, suggesting either positive or negative effects of inducement on maize yield and net income of farmers.

Tables 3 and 4 present the conditional mean effect of inducement on maize yield and net income by treatment type. The tables report the results of three estimators' estimates of the

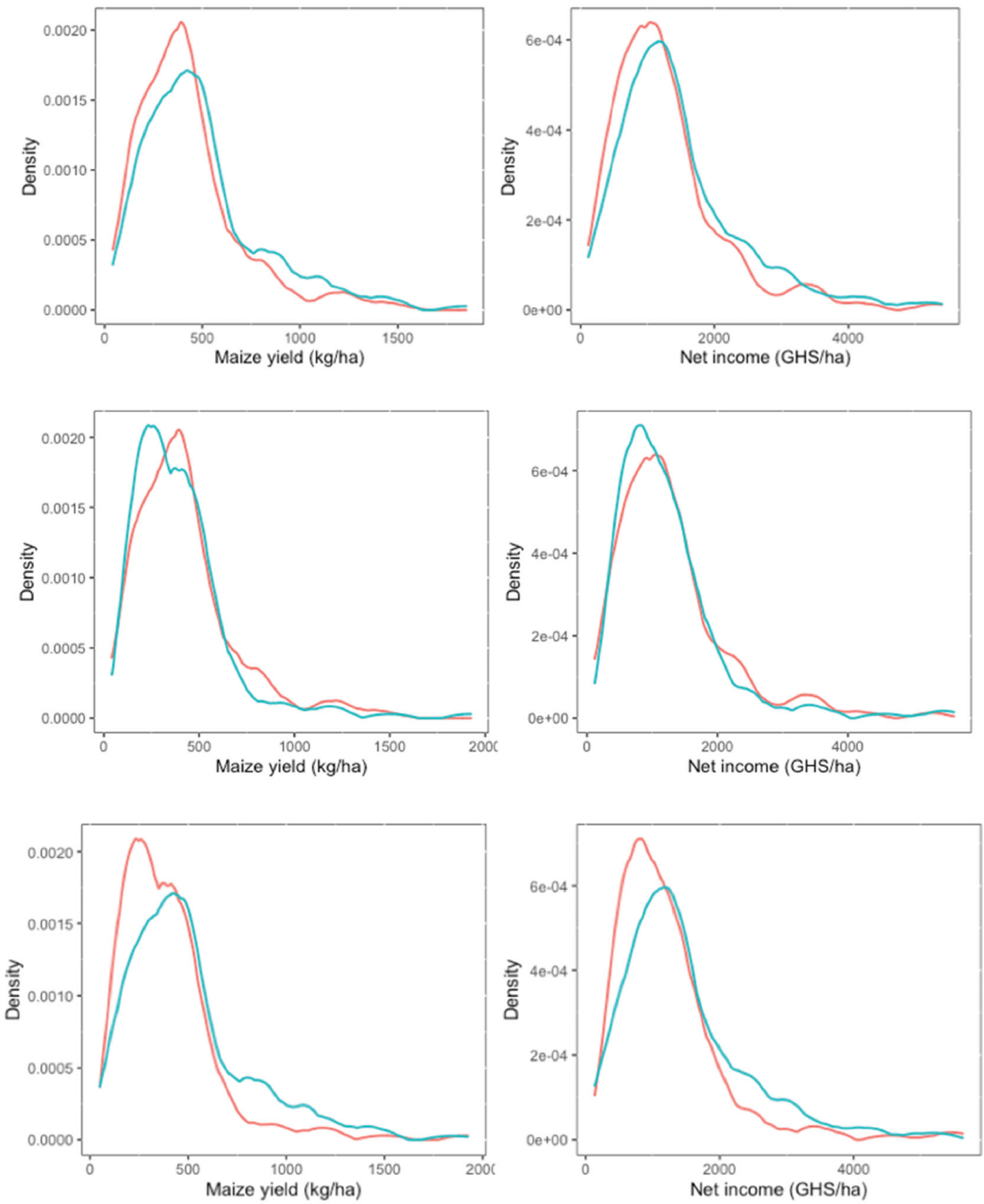

Figure 1. Kernel density curves of maize yield and net income of farmers for continued versus non-intervention (top panel), phased-out versus non-intervention (middle panel), and continued versus phased-out (bottom panel) communities. The red curve denotes maize yield and net income of farmers for either phased-out (bottom panel) or non-intervention (top and middle panels) communities. The green curve represents maize yield and net income of farmers in either continued (top and bottom panels) or phased-out (middle panel) communities.

average effect under different estimation assumptions. Table 3 presents the mean effect of inducement for continued versus non-intervention and phased-out versus non-intervention, respectively. Generally, the estimates are qualitatively the same under each treatment type. Specifically, the MTE estimates indicate that the continuous inducement increases maize yield

Table 3. Mean effect of inducement on maize yield and net income by treatment type

Estimator	Continued vs Non-intervention		Phased-out vs Non-intervention	
	Log maize yield (kg/ha)	Log net income (GHS/ha)	Log maize yield (kg/ha)	Log net income (GHS/ha)
MTE	0.321**	0.363**	0.103	0.004
	(0.137)	(0.134)	(0.124)	(0.114)
IPW-Lasso	0.156*	0.148*	−0.057	−0.020
	(0.062)	(0.073)	(0.058)	(0.059)
Kernel matching	0.146**	0.155**	−0.066	−0.037
	(0.067)	(0.067)	(0.062)	(0.063)
Observations	443		440	

Notes: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$ denote significant at 10 percent, 5 percent, and 1 percent, respectively. Standard errors in parentheses. \$1 = 5.4 Ghana cedis (GHS) at the time of the survey. The critical hidden bias for the kernel matching estimator ranges between 1.1 and 1.5 for continued versus non-intervention, and 1.1–3.5 for phased-out versus non-intervention. All the estimators estimate the average treatment effect on the treated (ATT) under difference estimation assumptions. The marginal treatment effect (MTE) accounts for heterogeneity in both the treatment effect and farmers' unobserved factors, whereas the inverse propensity score weighting with lasso regression (IPW-Lasso) and the kernel matching account for heterogeneous treatment effect only.

and net income of farmers in the continued community by about 32 per cent and 36 per cent, respectively. The estimates also suggest that the past inducement had either a positive or a negative effect on maize yield and net income of past induced farmers, albeit not significant. On the whole, Table 3 implies a positive effect of inducement on maize yield and net income of farmers in the continued communities.

4.2.1. The gains or losses with the continuation of the inducement. Table 4 reports the mean effect of inducement on maize yield and net income of farmers for continued versus phased-out communities. The table suggests a positive and significant effect of continuous inducement on maize yield and net income of farmers in the continued communities. For example, the MTE estimates indicate that continuous inducement increases maize yield and net income of continuously induced farmers by about 64 per cent and 53 per cent, respectively, on average. This finding underscores the effect of persistence of learning and inducement on maize yield and net income of farmers in the continued communities.

4.3. Heterogeneous effects

Figure 2 illustrates the distributional effects of the inducement on maize yield and net income of farmers for continued versus non-intervention (top panel), phased-out versus non-intervention (middle panel), and continued versus phased-out (bottom panel) communities. The point and the vertical lines denote the point estimate and the 90 per cent confidence intervals, respectively. The grey line from zero represents our reference line, and it helps evaluate the differences of the quantile effects from zero.

Overall, the quantile estimates indicate that the distributional effects of the inducement on maize yield and net income of farmers vary across the quantile indexes. For example, the top panel indicates positive effects of inducement on maize yield and net income of continuous induced farmers. In particular, we find significant inducement effects at quantile 10 and above quantile 70 for maize yield and below quantile 30 and above quantile 70 for net income.

In addition, the middle panel suggests positive effects of past inducement on maize yield and net income of farmers below quantile 30 for maize yield and net income, respectively. More specifically, we find significant effects of past inducement on maize yield and net income of farmers

Table 4. Mean effect of continuous inducement

	Continued vs Phased-out	
Estimator	Log maize yield (kg/ha)	Log net income (GHS/ha)
MTE	0.640**	0.539*
	(0.315)	(0.299)
IPW-Lasso	0.212**	0.169*
	(0.066)	(0.066)
Kernel matching	0.173**	0.144**
	(0.069)	(0.070)
Observations	341	

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ denote significant at 10 percent, 5 percent, and 1 percent, respectively. Standard errors in parentheses. \$1 = 5.4 Ghana cedis (GHS) at the time of the survey. The critical hidden bias for the matching estimator ranges between 1.1 and 1.7. All the estimators estimate the average treatment effect on the treated (ATT) under difference estimation assumptions. The marginal treatment effect (MTE) accounts for heterogeneity in both the treatment effect and farmers' unobserved factors, whereas the inverse propensity score weighting with lasso regression (IPW-Lasso) and the kernel matching account for heterogeneous treatment effect only.

below quantile 20. This result suggests that farmers at the lower quantile indexes still benefit from the past inducement than other farmers. It is worth mentioning that this finding was masked at the mean level.

Finally, the bottom panel reveals positive effects of continuous inducement on maize yield and net income of farmers across the quantile indexes. Estimates also indicate positive and significant effects of inducement below quantile 50, implying that the continuously induced farmers at these quantile indexes benefited greatly from the continuous inducement.

4.4. Is the inducement cost effective?

We estimated the cost effectiveness of conditional inducement *vis-a-vis* organising a farmer field day to stimulate farmers' adoption of SI practices. We used the average net income of maize yield derived by an induced and a non-induced farmer from a continued community to conduct a cost-benefit analysis of inducing 30 farmers through a conditional inducement and a farmer field day, respectively. Tables A5 and A6 present a cost-benefit analysis for the two scenarios. Table A6 indicates that the conditional inducement generates a benefit of about 44, 452 GHS, a total cost of around 8000 GHS, and a net benefit of about 36,452 GHS, leading to a benefit-cost ratio of 5.56. In contrast, inducing farmers to adopt SI practices via a farmer field day generates a benefit of about 35,600 GHS, a total cost of around 7320 GHS and a net benefit of about 28,2780 GHS, resulting in a benefit-cost ratio of 4.86 (Table A6). In summary, the two tables suggest that the conditional inducement is somewhat more cost effective than a farmer field day.

5. Discussion

The estimates presented in this paper provide evidence that the conditional inducement of farmers affected crop productivity and net income of farmers. Our findings revealed that the continuous inducement increased maize yield and net income of farmers in the continued communities. Distributional estimates imply that the effects of the conditional inducement vary across the households. Although our average estimates indicated insignificant effect of past

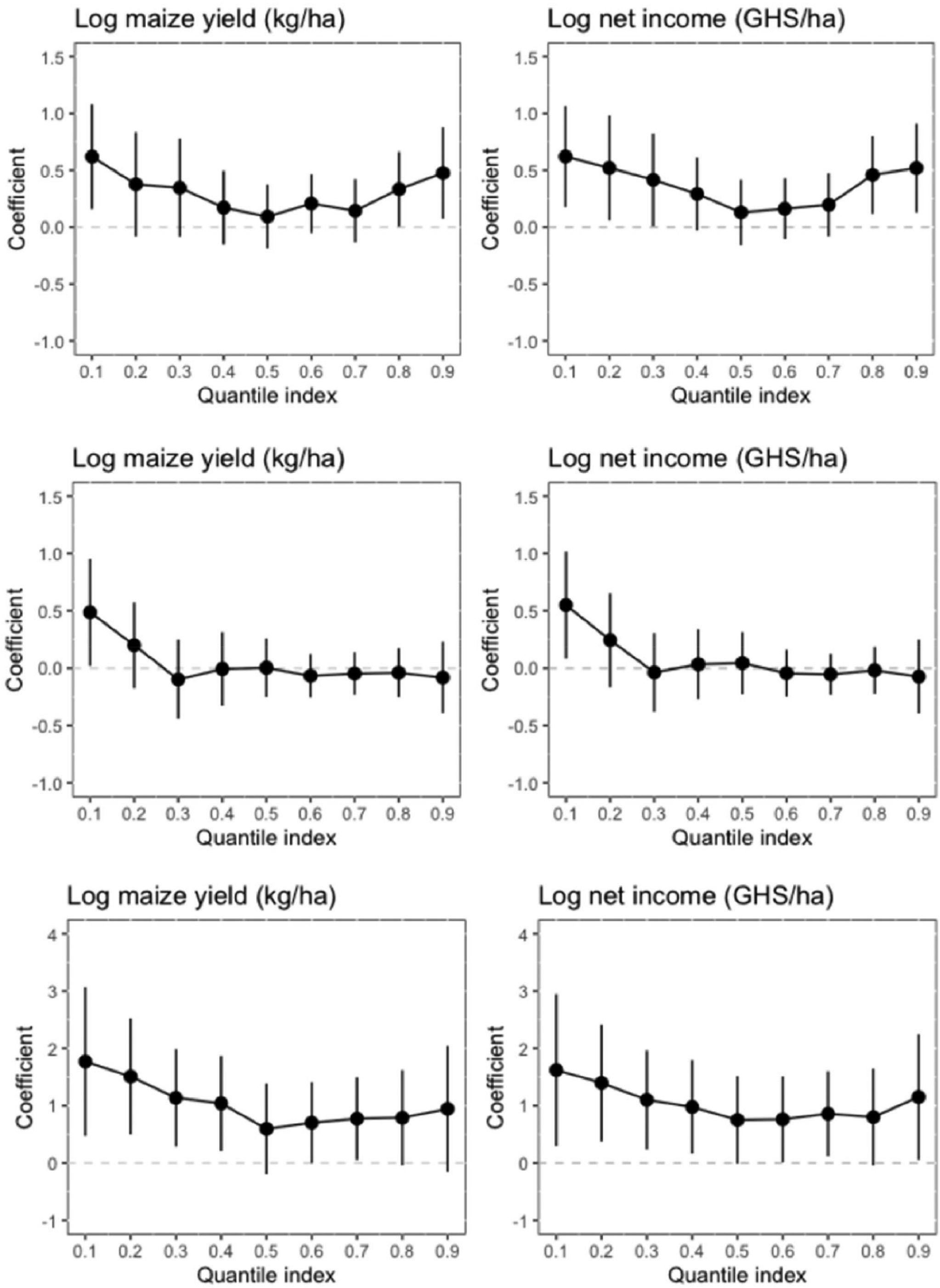

Figure 2. Distributional effects of inducement on maize yield and net income of farmers for continued versus non-intervention (top panel), phased-out versus non-intervention (middle panel), and continued versus phased-out (bottom panel) communities.

inducement on maize yield and net income of farmers in the phased-out communities, our distributional estimates imply that past induced farmers at the lower quantile distribution still benefit from the past conditional inducement.

Our findings complement previous studies (for example, Grabowski et al., 2016; Suri, 2011) that tried to uncover the reasons why farmers' dis-adopt agricultural technologies post intervention. In addition, the importance of social learning in the diffusion of new technologies have been highlighted by many studies (for example, Acemoglu, 2012; Foster & Rosenzweig, 1995; Romer, 1986). Agricultural research and extension systems have used social learning to encourage adoption and diffusion of new technologies (Bindlish & Evenson, 1997; Conley & Udry, 2010; Evenson & Westphal, 1995; Rogers, 2010).

Our results reveal that the duration and persistence of intervention matter most if adoption and diffusion of new technologies would have to be achieved through social learning. This is because farmers need to experiment with new technologies to be able to understand the correct inputs combination required to achieve the optimum benefits. Indeed, several factors (for example, climate change, pests and diseases, socio-cultural systems) dictate when farmers can realise these optimum benefits. Conditioning of incentives or inputs also induces farmers to follow recommended practices and thus increases the relative advantage of new technologies (Rogers, 2010). The rates of adoption and diffusion of new technologies can be increased if the quality of information (for example, fertiliser rates, planting distance, expected yield) conveyed from a farmer to another farmer is not undermined by lack of knowledge about the new technologies on the side of the sender. This can be avoided if the sender is abreast with how the new technologies are implemented. This underscores the importance of persistence of intervention in any programme.

Our findings further support previous calls for examining the effect of intervention beyond the average effect (Bitler, Gelbach, & Hoynes, 2006; Chernozhukov & Hansen, 2005; Heckman, Tobias, & Vytlacil, 2001; Mogstad & Torgovitsky, 2018). For example, the distributional estimates indicated that the withdrawal effect of the inducement is heterogeneous with few farmers benefiting from the previous inducement. This result could be attributed to differences in the learning rates among farmers. It is worthwhile to note that this finding was masked at the average level.

Our results also indicate that farmers at the lower quantile distribution still benefit after the withdrawal of the inducement, suggesting that to maximise return on scaling up investment would require targeting of these households. In other words, similar programmes can be terminated after three years provided low resource endowed farm households are targeted during diffusion. Indeed, a current study has shown that targeting these households would generate the highest marginal benefits (Mellon Bedi et al., 2021). Moreover, recent on-farm field experiments, managed by both farmers and researchers across northern Ghana, suggest positive effect of SI practices on maize yield and net income after three years (Rahman et al., 2021). This finding could indicate that continuous inducement in the continued communities can be withdrawn since benefits from the SI practices can be realised after 3 years. However, the withdrawal should be conducted in an approach (for example, from highly resource to the lowest resource endowed communities) to avert any adverse shocks it may have on farmers. In addition, more research is warranted on optimal time frames for interventions in the future, since such research would have practical value as it could significantly increase impacts and cut costs of interventions.

6. Conclusion

This paper examined the effects of conditional inducement on maize yield and net income of farmers. Our findings imply that agricultural programmes aimed at increasing crop yield and net income of farmers can be achieved through the diffusion of SI practices. The results indicate that conditioning of inputs or incentives given out to farmers can be used to stimulate farmers' adoption. A practical policy implication is for example, instead of governments and development agencies offering farmers free inputs to motivate farmers' adoption during diffusion of new technologies, the inputs could be conditioned on farmers' adoption of recommended practices. Moreover, it should be noted that persistence of the intervention matters, and must not be overlooked in interventions that involve gaining experience and learning. Finally, the results suggest that agricultural programmes aimed at stimulating farmers' adoption of new technologies should not only focus on overcoming the immediate obstacles to adoption through the provision of inputs, but rather should also focus on sustaining adoption. This would require the provision of support services (for example, improvement of farmers' learning through extension services) and conditioning of programme supports (for example, social protection programmes) to the adoption of the new technologies (Holden, Barrett, & Hagos, 2006; Pannell, Llewellyn, & Corbeels, 2014; Sitko, Scognamillo, & Malevolti, 2021). This implies that an effective collaboration between relevant government ministries (for example, social welfare and agriculture) and development agencies in the diffusion process will be much needed in sustaining adoption post intervention.

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Data availability statement

Data, stata and R codes are available upon request. Data can also be accessed in the future at https://dataverse.harvard.edu/dataverse/IFPRI.

Notes

1. These are events organised at the end of each cropping season with the aim of demonstrating new agricultural technologies to farmers. Farmers are brought together around field experiments guided by an extension agent or a researcher.
2. It relates to the combination of multiple inputs in an integrated way with the aim of increasing crop productivity, while at the same time lowering the environmental impacts.

3. Quasi randomised-phaseout designs are really scarce, especially in agriculture. The only exception include Fishman, Smith, Bobić, and Sulaiman (2017) and Carter, Laajaj, and Yang (2016).
4. See https://africa-rising.net
5. 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 an effect size of 0.20.

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