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Disseminating sustainable intensification practices: Empirical evidence from Ghana

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Abstract

Adoption of sustainable intensification (SI) of agricultural practices is essential for increasing food production in more sustainable way. Dis-adoption of agricultural technologies is pervasive among smallholder farmers in sub-Saharan Africa after withdrawal of most programme interventions. Based on data elicited from households in northern Ghana, this study i) examines alternative ways of inducing farmers into adopting SI practices, ii) determines the marginal farm household entrants that must be targeted during scaling up and -out SI practices, and iii) identify the farm households that benefited most from SI adoption during diffusion. Econometric approaches that account for sample selection issues were used in addressing the objectives of the study.

The empirical results show that inducing farmers to adopt SI practices resulted in an increase in maize yield and net income of farmers. Results also suggest that the continuous inducement of farmers led to positive and significant increase in maize yield and net income of induced farmers. Point estimates reveal that stopping the inducement could have led to a decrease in maize yield and net income of induced farmers. The findings also indicate that farmers' resource endowment and unobserved factors influence the marginal benefits of adopting SI practices, and that scaling up SI practices will favour marginal farm household entrants associated with the least probability of adoption based on observed socioeconomics characteristics. Finally, the results show that the adopters that benefited most from SI adoption during its diffusion are much more likely to live in highly resource endowed farm households with relatively younger household heads and fewer household members, and are more likely to travel longer distances before reaching the nearest weekly market and motorable road.

Overall, the study provides empirical evidence that the adoption of SI practices enhances farm performance and household welfare, and that scaling up should be targeted. The study also suggests that the provision of support services is a necessary condition for sustaining adoption and thus collaboration between programme interventions with key government ministries and private business mechanisation firms are needed in the scaling up policy decision-making.

Zusammenfassung

Die Einführung nachhaltiger Intensivierung landwirtschaftlicher Praktiken ist für die Steigerung der Nahrungsmittelproduktion auf nachhaltigere Weise unerlässlich. Die Disadoption von Agrartechnologien ist häufig unter Kleinbauern in Afrika südlich der Sahara weit verbreitet, nachdem Programminterventionen eingestellt wurden. Diese Studie basiert auf Daten von 700 bäuerlichen Haushalten, die im Rahmen eines landwirtschaftlichen Forschungsprogramms zur Entwicklung im Norden Ghanas erhoben wurden. In dieser Studie werden i) alternative Möglichkeiten untersucht wie Landwirte dazu gebracht werden können, neue landwirtschaftliche Technologien zu übernehmen, ii) die marginalen landwirtschaftlichen Haushalte bestimmt, die bei der Einführung von SI-Praktiken angesprochen werden müssen, und iii) die landwirtschaftlichen Haushalte ermittelt, die am meisten von der Annahme von SI-Praktiken im Norden Ghanas profitiert haben. Um die Ziele der Studie zu erreichen wurden mehrere ökonometrische Methoden eingesetzt, welche die Selektionsverzerrung der Stichprobe adressieren.

Die empirischen Ergebnisse zeigen, dass die Anregung der Annahme der SI-Praktiken zu einem Anstieg der Maiserträge und des Nettoeinkommens der Landwirte führte. Die Ergebnisse deuten auch darauf hin, dass die kontinuierliche Anregung der Landwirte zu einem positiven und signifikanten Anstieg der Maiserträge und des Nettoeinkommens der geförderten Landwirte führte. Punktschätzungen zeigen, dass die Beendigung der Anreize zu einem Rückgang der Maiserträge und des Nettoeinkommens der angeregten Landwirte geführt haben könnte. Die Ergebnisse deuten auch darauf hin, dass die Ressourcenausstattung der Landwirte und unbeobachtete Faktoren den Grenznutzen der Einführung von SI-Praktiken beeinflussen und dass die Ausweitung von SI-Praktiken marginale landwirtschaftliche Haushalte begünstigt, die auf der Grundlage der beobachteten sozioökonomischen Merkmale die geringste Wahrscheinlichkeit der Einführung haben. Schließlich zeigen die Ergebnisse, dass die "Adopter", die auf der Grundlage des Nettoeinkommens aus Mais- und Leguminosenerträgen während der SI-Diffusion am meisten von der Adoption profitiert haben, sehr viel wahrscheinlicher in ressourcenstarken landwirtschaftlichen Haushalten mit relativ jüngeren Haushaltsvorständen und weniger

Haushaltsmitgliedern leben. Außerdem müssen sie mit größerer Wahrscheinlichkeit längere Strecken zurücklegen, bevor sie den nächsten Wochenmarkt und die nächste befahrbare Straße erreichen.

Insgesamt liefert die Studie empirische Belege dafür, dass die Einführung von SI-Praktiken die landwirtschaftliche Leistung und das Wohlergehen der Haushalte steigert und dass eine Skalierung und den Ausbau angestrebt werden sollte. Die Studie deutet auch darauf hin, dass die Bereitstellung von Unterstützungsdiensten eine notwendige Bedingung für eine nachhaltige Einführung ist und dass daher eine Zusammenarbeit zwischen wichtigen Ministerien und privaten Mechanisierungsunternehmen bei der politischen Entscheidungsfindung für die Skalierung und den Ausbau erforderlich ist.

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Abbreviations

Africa-RISING	Africa Research in Sustainable intensification for the Next Generation
ATE	Average Treatment Effect
ATT/TT	Average treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
APE	Average Partial Effect
IITA	International Institute of Tropical Agriculture
IPM	Integrated Pest Management
IPW	Inverse Propensity Score Weighting
ISFM	Integrated Soil Fertility Management
IV	Instrumental Variable
IVQR	Instrumental Variable Quantile Regression
LASSO	Least Absolute Shrinkage and Selection operator
LATE	Local Average Treatment Effect
MTE	Marginal Treatment Effect
MPRTE	Marginal Policy Relevant Treatment Effect
OLS	Ordinary Least Squares
PRTE	Policy Relevant Treatment Effect
PE	Partial Effect
QTE	Quantile Treatment Effect
QR	Quantile Regression
QE	Quantile Effect
SSA	Sub-Saharan Africa
SI	Sustainable Intensification
SPE	Sorted Partial Effect or Sorted Predictive Effects
TUT	Treatment Effect on the Untreated
USAID	United State Agency for International Development
2SLS	Two Stage Least Squares

Chapter 1: General introduction

1.1. Motivation

The Sustainable Development Goal 2 (zero hunger) of the United Nation places much emphasis on Africa where future population is estimated to increase in the face of expected strong climate change impacts (Niang et al., 2014). For example, the population in sub-Saharan African (SSA) countries is anticipated to increase from its current 1.07 billion to about 3.78 billion by the end of the century (United Nation, 2019). This suggests that the demand for food, feed, and fibre within the sub-region will go up in the near future (Montpellier Panel, 2013; Vanlauwe et al., 2019).

Generally, agricultural production in SSA has improved over the past decades due to cultivation of more land rather than increases in land productivity(Sanchez, 2002,Giller, 2020). Nevertheless, there is already a large gap between what farmers are currently producing and the yields farmers could derive, indicating a major opportunity to increase food production (Tittonell and Giller, 2013; Van Ittersum et al., 2016). But this is likely to be impeded by poor fertile soils that typify most soils in SSA due to over cultivation and inadequate use of mineral fertilisers (Buresh et al., 1997; Giller et al., 1997). Conversely, relying solely on the application of mineral fertilisers to improve soil nutrients without paying attention to the soil organic matter cannot also sustain food production (Giller, 2020).

Poor institutional structures and land constraints are likely to impede investments (e.g. finance and labour) into food production (Giller, 2020). Since food in SSA is mainly produced by smallholder farmers (Dixon et al., 2001; Giller, 2020), current rapid increases in urban and rural populations are likely to impose pressure on agricultural lands leading to smaller farms (Jayne et al., 2014; Muyanga and Jayne, 2014), and thus for farmers to be able to continue to produce food as well as maintain soil organic matter would require intensification of agricultural practices in a more sustainable way.

Governments, donor agencies and research institutions continue to help with developing policies and disseminating new agricultural technologies and practices with the aim of helping farmers to improve upon their agricultural productivity. Amongst them, sustainable intensification (SI) of agricultural practices has been promoted in recent times due to its potential to enhance farmers' crop and soil productivity in a more sustainable manner.

SI involves the combination of multiple inputs and technologies in an integrated way to improve agricultural productivity, while at the same time increasing the contribution to natural capital and environmental services (Godfray et al., 2010; Pretty, 1997). It is also connected to less land cultivation, maintaining untouched habitats as well as improving the resilience of agroecological systems (Godfray et al., 2010; Pretty, 1997). More specifically, SI involves the combination of yield-enhancing measures (e.g. use of improved crop varieties), yield-protective measures (e.g. integrated pest management) and soil-protective measures (e.g. conservation agriculture, crop rotation)(Petersen and Snapp, 2015). Overall, SI aims at replicating the benefits associated with the Asian Green revolution with much more attention on reducing the negative environmental externalities (Pretty, 1997;The Montpellier Panel, 2013).

Just like most countries in SSA, the farming system in Ghana is very heterogeneous in terms of farmers' resource endowment and agroecological conditions (Giller et al., 2011; Kuivanen et al., 2016). The latter affects the type of crops grown by farmers (MoFA, 2017). For example, cereals and legumes are greatly produced in the Savannah agroecological zone, while tree crops, fruits, root and tubers, and vegetables are mostly from the forest and the coastal zones. Cereals, mainly maize and rice, are the major staples in Ghana (MoFA, 2017). Although cereals are abundantly produced in the Savannah agroecological zone, the soils in the zone are poor and prone to soil erosion, indicating that soil fertility improvement is much needed (Tetteh et al., 2016), and thus the diffusion of sustainable agricultural practices such as SI practices could be one of the various ways to enhance farmers' soil and crop productivity, household welfare and food security in the agroecological zone.

1.2. Problem statement

In recent times, several SI practices have been disseminated across SSA with findings showing positive outcomes: increases in crop yields, farm incomes, and enhancement of farmers' soil productivity (e.g. Kim et al., 2019; Rahman et al., 2021). Nevertheless, previously disseminated agricultural technologies and practices (e.g. conservation of agricultural practices) in SSA have either been less adopted or dis-adopted by farmers, although the technologies and practices bear positive outcomes (e.g. Moser and Barrett, 2003; Giller et al., 2009; Grabowski et al., 2016, Bouwman et al., 2021).

Several reasons such as lack of information (Ashraf et al., 2009), differences in agroecological conditions (Giller et al., 2011), high transaction costs due to poor road networks (Karlan et al., 2014), lack of access to agricultural inputs (Emerick and Dar, 2021) and inadequate use of mineral fertilisers (Duflo et al., 2011) have been identified to be some of the causes of low adoption rates.

Besides, the dissemination approach used to spur farmers into adopting agricultural technologies and practices affect farmers' adoption decision-making (Emerick and Dar, 2021). Farmer field day and the use of mobile technology dominate current dissemination methods used in developing countries, especially in SSA (Emerick and Dar, 2021). However, studies in Malawi and Kenya have shown that farmer field days are less effective in motivating farmers into adopting agricultural technologies and practices (Fabregas et al., 2017; Maertens et al., 2021). In addition, the use of mobile technology in disseminating agricultural technologies and practices in SSA is still in its nascent stage (von Braun, 2018). Besides, studies on alternative methods of inducing farmers into adopting agricultural technologies and their long-term effects are very scanty in the adoption literature.

Furthermore, the literature on technology adoption in SSA focused on average effect of adopting agricultural technologies and practices (e.g. Abdulai and Huffman, 2014; Bellon et al., 2020; Khonje et al., 2015; Kotu et al., 2017; Manda et al., 2016), although the farming systems in SSA are very heterogeneous in terms of farmers' resource endowment and agroecological conditions (Giller et al., 2011). Few studies have emphasised the heterogeneous effects of adopting new agricultural technologies and practices (e.g. Issahaku and Abdulai, 2020; Michler and Josephson, 2017). However, the average and heterogeneous effects barely contribute to scaling up policy decisions-making or predicting which farm households at the margin of adoption would benefit most when targeted at scale. This is of great policy relevance since scarce resources are much more likely to be wasted when wrong farm households are targeted during scaling up and-out. Moreover, the heterogeneous nature of farming systems in Ghana just like most countries in SSA suggests the need to target agricultural technologies and practices at scale.

Finally, the majority of the adoption literature focuses less on the heterogeneity in the treatment effects of adopting agricultural technologies and practices at the subpopulation of adopters, as well as the characteristics of the farm households that benefited most and least from adoption. Failure to account for the heterogeneity at the subpopulation level in scaling up decision-making may contribute to mistargeting of new agricultural technologies and practices, which may lead to less adoption or dis-adoption in the future.

1.3. Research questions

Based on the identified research gaps, this study examines the adoption and scaling up effects of disseminating SI practices on farm performance and household welfare. Specifically, the study aims at addressing the following research questions:

1. Are there alternative ways of incentivising farmers into adopting agricultural technologies?
2. Which farm households should be targeted during scaling up of agricultural technologies such as SI practices?
3. Who benefits most and least from SI adoption during diffusion?

1.4. Conceptual framework

Figure 1.1 illustrates the conceptual framework summarising how the study intends to address the research questions and objectives of the study. Generally, farmers can be induced to adopt SI practices via the provision of support in the form of inputs (e.g. improved seeds), which can spur their decision to adopt. Since SI involves the inclusion of soil and yield protective measures, farmers' adoption of maize-legumes intercropping would enhance ecosystem services (e.g. water and air regulation) and soil fertility (Giller, 2001; Vanlauwe et al., 2010). For example, legumes are able to capture and fix atmospheric nitrogen into the soil through its symbiosis relationship with rhizobia (Giller, 2001; Vanlauwe et al., 2010). In addition, legumes help control weeds, pests and plant diseases (Franke et al., 2018).

The study expects that the improvement in soil productivity would translate into increases in crop yields and enhancement of available food in farm households. Farm households can also sell portions of their harvest for income and use the derived income to purchase other food items (e.g. egg, meat) and non-food products (e.g. clothes, medicine). The study envisages that these benefits would lead to improvement in farm household welfare. Finally, the inclusion of legumes into maize-based systems and the use of improved crop varieties (e.g. drought tolerant maize) can help farmers diversify their outputs, as well as mitigate the adverse effects of climate change and price volatility.

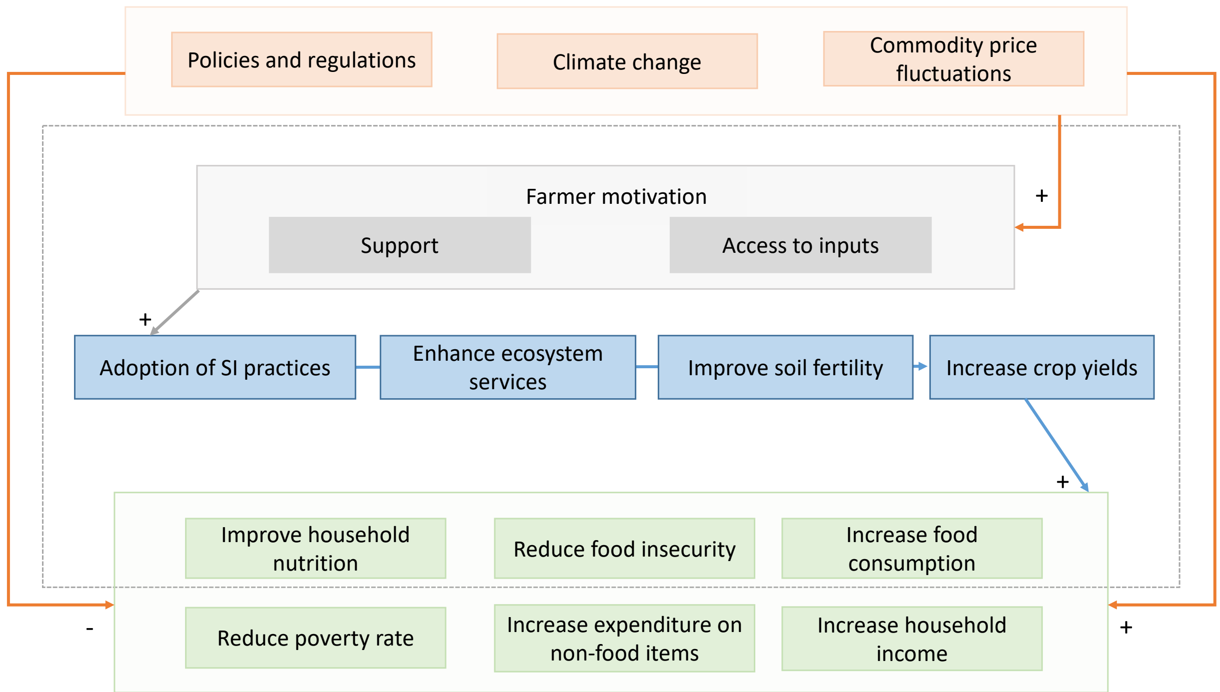

Figure 1.1: Conceptual framework. The gray boxes represent motivational items require for farmers to adopt SI practices. The blue boxes show the effects of adopting SI practices. The green boxes are the benefits of increase in crop yields and net returns. The orange boxes are the external factors that can affect adoption of SI practices. The arrows denote positive or negative effect. The dashed lines represent the farm household boundary.

1.5. Research methods

1.5.1. Study area

Ghana is divided into four agroecological zones: the Coastal Zone, the Forest Zone, the Southern Zone (or the transition zone), and the Savannah Zone (Nin-Pratt and McBride, 2014). Generally, the amount of rainfall per year decreases from about 2200 to 900 mm as one transition from the first three zones to the Northern Zones. The first three zones are also characterised by a bimodal rainfall pattern, while the Savannah Zone is characterised by a unimodal rainfall pattern (MoFA, 2017). The Savannah Zone is sub-divided into the Guinea and the Sudan savannah agroecological zones. The zones are characterised by the Northern region, the Upper East region and the Upper West region.[1]

The majority of the farm households across the regions are smallholder farmers who cultivate cereals (e.g. maize, rice, millet), legumes (e.g. bean, cowpea, soybean), root and tubers (e.g. yam, cocoyam) and vegetables. Maize production is common in both the Northern regions (Northern, Savannah, and North-West) and the Upper West region than the Upper East region, where drought tolerant crops such as sorghum and millet are cultivated by most farmers, even though maize production in the region is gradually increasing (Ellis-Jones et al., 2012). Most crops across all the regions are produced under rain-fed agriculture. Small and large ruminants (e.g. cattle, sheep, poultry (e.g. guinea fowl and chicken) and pigs are also raised by some farm households in the regions. Nevertheless, poverty levels among smallholder farmers in the regions are the highest in the country (Cooke et al., 2016; MoFA, 2017). Moreover, farmers in the regions are more vulnerable to drought and other related climate shocks compare to other regions in the country (Ellis-Jones et al., 2012).

1.5.2. The Africa RISING programme

The Africa Research in Sustainable Intensification for the Next Generation (Africa-RISING) was sponsored by the United State Agency for International Development (USAID) as part of the Feed-the-Future-Initiative with the sole aim of moving farmers out of hunger and poverty through sustainably intensified (SI) farming systems. The programme's objective was to improve farmers' crop productivity, farm incomes and food and nutrition security, especially for women and children.[2] The programme was set up in Ghana, Mali, Tanzania, Zambia, Malawi, and Ethiopia.

The Africa-RISING programme was launched in 2012 across northern Ghana. The programme was designed and implemented in a quasi-experimental format (Tinonin et al., 2016, Kotu et al., 2017;

[1] The Northern region has been sub-divided into three regions: Savannah, North East and Northern.
[2] https://africa-rising.net/

Bellon et al., 2020). Prior to the start of the programme, the main administrative districts in the regions were stratified into six domains based on market access and length of day period, a proxy of the agricultural potentials of the region (Guo and Azzarri, 2013). Fifty communities were sampled across the six domains. Twenty-five communities were purposely sampled from the six domains to receive interventions, whereas the rest, randomly sampled, were assigned as non-intervention communities (Guo and Azzarri, 2013; Tinonin et al., 2016).

To improve the cereal-legume based farming system across the regions, farmers were trained on several SI practices aimed at improving crop yield, farm income and soil productivity with the aid of a technology park. The technology park served as a learning centre for demonstration and dissemination of the SI practices. The park was set up in all the intervention communities. Examples of the SI practices demonstrated included efficient fertiliser application, proper crop spacing, line sowing, use of improved seed varieties (e.g. drought tolerance maize), and how to incorporate legumes (e.g. cowpea, groundnut) into cereal based cropping system.

The programme also 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 and technologies from the park. It is worth noting that the items were not randomly assigned to the farmers. The programme further assisted the incentivised farmers in establishing the SI practices on their farms through its collaboration with the government extension agents or by assigning officers to the communities where there are no assigned government extension agents. Forty farm households per community, on average, were incentivised. Farmer field days were also organised in the intervention communities with the aim of exposing other farmers within and around the intervention communities to the SI practices. Nonetheless, in 2016, the programme discontinued its activities in 13 communities due to limited funding from the major donor. Figure 1.2 illustrates the spatial distribution of the Africa-RISING intervention and non-intervention communities.

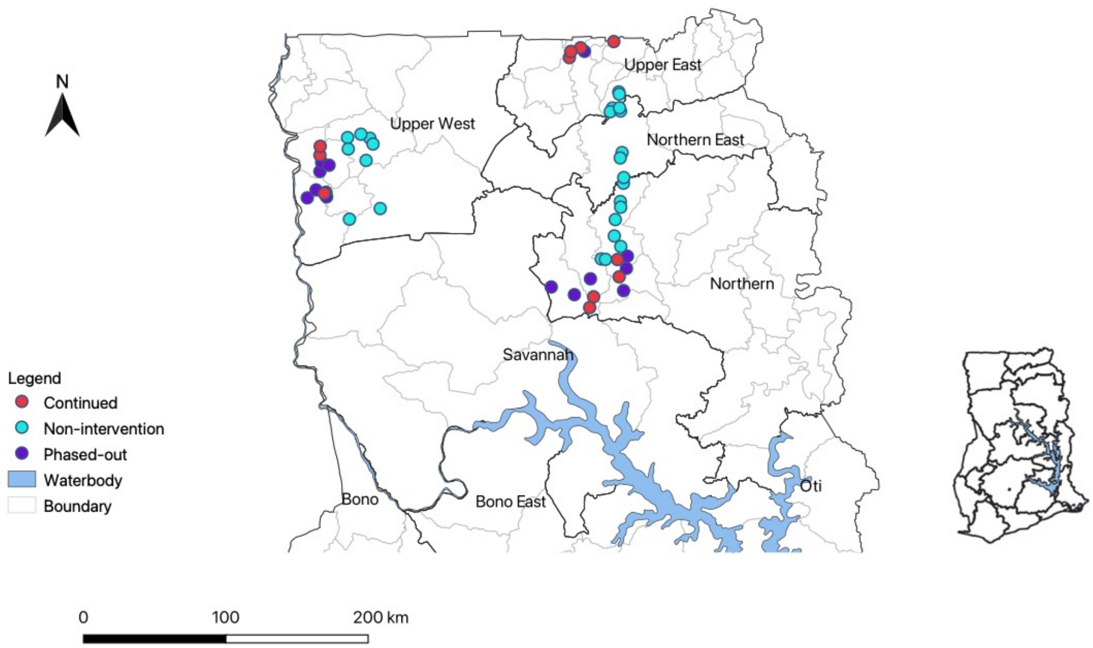

Figure 1.2: Africa-RISING intervention communities. Author's own map.

1.5.3. Data collection

The data for this study was obtained as a follow-up of the Ghana Africa-RISING Baseline Survey conducted in 2014 (Tinonin et al., 2016), where 1248 farm households were surveyed across both the intervention and non-intervention communities. A follow-up study within the same period as in the baseline study was conducted. However, a three-step approach was adopted in sampling the households given the limited budget for the study. First, a power analysis[3] was conducted to establish the appropriate sample size for the follow-up study, which led to a total sample size of 700 households. Second, we adjusted the sample size of the regions and other administrative divisions to match the baseline information. Finally, a random sampling method was used to sample the farm households from the list of farm households surveyed during the baseline study. Overall, we sampled and interviewed 271 households from the non-intervention communities,

[3]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 of attrition and non-responses to questions.

and 429 from the intervention communities (i.e. 212 farmers from the continued communities, 217 farm households from the phased-out communities).

Prior to the survey, enumerators were hired and trained for about 6 days. Under the author's supervision, they conducted face to face interviews with the sampled farm households. The farm households were interviewed on series of questions that covered socioeconomic characteristics, crop production, and food security.

1.6. The outline of the study

The rest of the thesis is organised into five main chapters. The Chapter 2 of the study examines alternative method of inducing farmers into adopting agricultural technologies. Here, the study exploits how the Africa-RISING programme was executed in addressing the objective. That is, the study contrasts continuous induced farmers with past induced and non-induced farmers to identify the effects of incentivising farmers into adopting SI practices and the effects on maize yield and net income of farmers. In addition, the study examines the distributional effects of the inducement on maize yield and net income of farmers under the three comparison treatment types.

Chapter 3 identify the farm households that need to be targeted during scaling up of SI practices. Specifically, under this section, the study exploits the heterogeneous nature of the farming systems in i) investigating whether farmers' resource endowment and unobserved factors affect the marginal benefit of adopting SI practices, ii) estimating the marginal and average benefits of adopting SI practices on maize yield and net income of farmers, and iii) predicting the farm households at the margin of adoption that need to be targeted at scale.

Chapter 4 identify the farm households that benefited most and least from SI adoption during its diffusion. Under this chapter, the study evaluates both the average and distributional effects of SI adoption on net income from maize and legume production and per capita food expenditure.

The study further examines the heterogeneity in the effects at the subpopulation of adopters as well as identify the characteristics of the adopters that benefited most and least from adoption.

Finally, chapter 5 concludes the thesis. The chapter provides summary and policy implications of the study.

Chapter 2: Stimulating innovations for sustainable agricultural practices among smallholder farmers – persistence of intervention matters[+]

Abstract

As part of the dissemination of sustainable intensification (SI) of agricultural practices in northern Ghana, farmers were conditionally induced with inputs to adopt sustainable intensification practices. We study the effects of the conditional inducement and its impact on maize yield and net income using a quasi-experimental phaseout design. We examine the effects of inducement by comparing continuous induced farmers with past induced and non-induced farmers. Our results show that the conditional inducement led to an increase in maize yield and net income of continuous induced farmers. Point estimates also indicate that the continuous induced farmers would have had their maize yields and net incomes decreased substantially if inducement had been discontinued. Distributional analyses reveal that the conditional inducement effects are heterogeneous, and past inducement still has a positive significant effect on maize yield and net income of past induced farmers, particular at the tail of the household distribution. We conclude that appropriate conditional inducement can stimulate adoption. Furthermore, the duration of interventions matter and that must not be overlooked in interventions that entail gaining experience and learning.

[+] The essay is co-authored by Bekele Hundie Kotu, Lukas Kornher and Joachim von Braun. I conceptualized the research, collected the data, developed the methodology, carried out the formal analysis, and wrote the manuscript. Bekele Hundie Kotu, Lukas Kornher and Joachim von Braun supervised the research, commented and edited the manuscript. A version of the essay has been published in the Journal of Development Studies under the same title.

2.1. 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 and beyond, especially in Sub-Saharan Africa (SSA). Governments, development agencies and research institutions have in the past developed policies and disseminated new agricultural technologies with the aim of helping smallholder farmers to increase their crop productivity and farm incomes. To stimulate adoption and sustain adoption among smallholder farmers during diffusion of agricultural technologies, development agencies and governments provide inputs and also enhance farmers' human capital in order to break the immediate barriers to adoption (Maggio et al., 2021). However, several studies (e.g. Arslan et al., 2017; Grabowski et al., 2016; Neill and Lee, 2001) have shown dis-adoption or poor adoption of agricultural technologies and practices among smallholder farmers after termination of most programmes.

Several reasons have been attributed to the low adoption rates, including lack of information (Ashraf et al., 2009), high transaction cost due to bad road network (Suri, 2011), lack of access to formal credit and insurance (Karlan et al., 2014), procrastination and inconsistencies in the use of inorganic fertilisers (Duflo et al., 2011), lack of access to inputs (Emerick and Dar, 2021), and differences in agroecological conditions (Bouwman et al., 2021; Giller et al., 2011).

Besides the factors highlighted above, dissemination methods used to spur farmers into adopting agricultural technologies have received less attention in the adoption literature (Emerick and Dar, 2021). Farmer field days and mobile technology currently dominate dissemination methods used in developing countries, particularly in SSA (Aker, 2011; Fafchamps and Minten 2012; Cole and 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 et al., 2017; Maertens et al., 2021). Moreover, the use of mobile technology in diffusing agricultural technologies in SSA is still in its nascent stage (von Braun, 2018).

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

We situate the study within the context of an agricultural programme in northern Ghana, where the agroecological conditions and the farming systems are highly heterogeneous just as in other regions in SSA (Giller et al., 2011; Kamau et al., 2018; Kuivanen et al., 2016). In addition, the regions in northern Ghana are typified by high rate of poverty among most farm households (Cooke et al., 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) programme currently implemented in northern Ghana. The same programme is also established in countries such as Mali, Ethiopia, Tanzania, Malawi and Zambia. The programme in Ghana was initially established in selected communities with their corresponding control communities, but in 2016 the programme dropped some of the intervention communities and continued with the rest due to inadequate funding from the major sponsor. We exploit these changes in project execution in addressing the objectives of the study.

Our comparisons of continued, phased-out and non-intervention communities provide answers to the ensuing policy-relevant questions: a) does inducing farmers stimulate adoption? b) do treatment effects from inducement vary across farm households? and c) do treatment effects decay at the same rate or vary across farm households in the absence of inducement? These policy-relevant questions are less addressed in the literature on technology adoption. However, finding answers to these questions can help policymakers develop new approaches to stimulate farmers' adoption of agricultural technologies, especially in SSA.

Overall, we contribute to small but growing research on how to scale up and -out agricultural technologies in SSA. More specifically, the study contributes to the adoption literature in several important ways. For example, our comparison of continuous induced farmers with past induced farmers helps answer the question on how should agricultural programmes that involve learning and experimentation by farmers be terminated? In addition, the study provides insight about which farm households are more likely to lose out from such termination, and finally, the study also provides information about what would have been the gains or losses among the continuous induced farmers if the programme had been discontinued in the continued communities.

Findings suggest a positive and significant effect of inducement on maize yield and net income of farmers in the continued communities. Distribution analysis implies that the inducement effects on maize yield and net income of farmers are very heterogeneous across the farm households. Point estimates also indicate that the continuous induced farmers could have had their maize yields and net incomes decreased, on average, by approximately 64% and 54%, respectively if the inducement had been discontinued. Finally, distributional analysis further reveals that past inducement still has a positive and significant effect on maize yield and net income of farmers at the lower quantile distribution.

The remaining sections develop as follows. Section 2.2 describes the Africa-RISING programme. Section 2.3 presents the data. Section 2.4 describes the conceptual framework and the methodology. Section 2.5 presents the results, and Section 2.6 presents the discussion and conclusion.

2.2. The Africa RISING programme

The Africa Research in Sustainable Intensification for the Next Generation programme (Africa-RISING)[4] was launched in northern Ghana in 2012. The objective was to help move farmers out of hunger and poverty through sustainably intensified (SI) farming systems. Prior to the beginning of the programme in 2012, the programme stratified the districts in the northern regions into six domains based on market access and agricultural potential of the regions (Guo and Azzarri, 2013). Fifty communities were then sampled across the six domains: 25 Intervention communities were purposely sampled to receive interventions, whereas the rest, randomly sampled, were assigned to non-intervention communities (Guo and Azzarri, 2013; Tinonin et al., 2016). The programme also ensured that the non-intervention communities did not share similar weekly markets with the intervention communities (Guo and Azzarri, 2013; Tinonin et al., 2016).

Furthermore, in the intervention communities, farmers were trained on how to improve upon their cereal based farming system through diffusion and demonstration of SI practices. The SI practices were demonstrated to farmers via the use of a technological park, sited across all the intervention communities. Examples of the SI practices demonstrated included proper fertiliser application, different crop spacing, line sowing, use of improve seed varieties, and how to incorporate legumes into maize based cropping system.

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. Overall. Forty farmers per community, on average, were incentivised across the intervention communities. Farmer field days were also organised within the intervention communities with the aim of exposing other farmers to the SI practices. However, in 2016, the programme discontinued its activities in 13 communities due to limited funding from the donor, and then proceeded to work with the rest of the 12 communities. Hereafter, we termed the 13 communities as phased-out and the rest as continued communities.

2.2.1. Study area

Ghana's northern regions can be classified under the Savanna agroecological zone, characterised by a unimodal rainfall pattern and support one growing season. Majority of the rural inhabitants are smallholder farmers who cultivate cereals (e.g. maize, rice, millet), legumes (bean, cowpea, soybean), root and tubers (e.g. yam) and vegetables. Most of these crops are produced under rain-fed agriculture. Small and large ruminants (e.g. cattle, sheep, goat), poultry (e.g. guinea fowl and chicken) and pigs are also raised by some farm households. Nevertheless, the poverty levels among smallholder farmers in the regions are the highest in the country (Cooke et al., 2016; MoFA, 2017).

2.3. Data collection

The current study is a follow-up of the Ghana Africa-RISING Baseline Survey conducted in 2014 (Tinonin et al., 2016), where 1248 farm households were surveyed across both the intervention and non-intervention communities. 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, which led to a total sample size of 652 farmers, but we increased the sample size to 700 farmers to address issues of non-responses to questions and attrition, although we did not face such 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 applied a simple random sampling method to sample our 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 farm households from the phased-out and 271 farmers from the non-intervention communities using our randomized list of sampled farmers from the baseline list. We note that the selected farmers from the continued and the 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 (this includes 40 and 48 farmers from the continued and phased-out communities, respectively).

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

2.3.1. Variables and summary statistics

The covariates used are factors identified to influence farmers' adoption of SI practices (Bellon et al., 2020; Kim et al., 2019; Kotu et al., 2017). These include information about the household head (e.g. gender, age, dependency ratio), dependency ratio, household size, farm size, extension services, group membership, herd size, off-farm income, number of productive assets own by the household, and time taken to reach the nearest motorable road and weekly market, etc. For our outcome variables, we focused on maize yield and net income. We concentrated on maize yield because it 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), whereas the net income was calculated by multiplying the average village price of 1kg of maize by the quantity harvested less the cost of production in Ghana cedis per hectare (GHS/ha).

Table 2.4 A1 reports the descriptive statistics of our sampled farm households. The table suggests that the majority of the 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% of the household heads cannot read and write and majority of the households sourced agricultural information from extension agents or NGOs. Furthermore, the average household size, livestock holdings and farm size of a given household are 9, 4, and 1.42, respectively. Finally, a farm household, on average, harvested about 1075 (kg/ha) of maize grains and derived an average net income of around 809 GHS/ha. Table 2.1 presents the mean differences in the farm household characteristics in the continued, phased-out, and non-intervention communities, respectively. On the whole, the table reveals significant differences in the household characteristics, implying that a simple mean difference between the outcome variables by community cannot be attributed to the inducement effect, since the estimate will be biased.

2.4. Theoretical framework and methodology

2.4.1. Theoretical framework

We base our theoretical framework on the model of learning about new agricultural technology of Conley and Udry (2010). Here, we assume that farmers already know the agroecological or the biophysical conditions of their surrounding (e.g. 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 them from the technology park and other farmers. The use of information from the technology park, which involves the combination of inputs coupled with their future related crop yields and profits will provide several information to farmers. In addition, a new set of knowledge will also be generated as farmers continue to implement the new technologies every season. We expect that the new information would help reduce the level of uncertainties and incomplete knowledge of the input combination. Furthermore, we surmise that incentivising farmers with conditions would motivate 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 and Huffman, 2014; Pitt, 1983).

2.4.2. Methodology

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

Table 2.1: Mean values of household characteristics by treatment status

Variable	(1) Continued Mean (SD)	(2) Phased-out Mean (SD)	(3) Non-intervention Mean (SD)	(4) 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	-0.037***	-0.091***
	(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 membership	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**	-1.100***	-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	-1.000***	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)			

Continued

Variable	(1) Continued Mean (SD)	(2) Phased-out Mean (SD)	(3) Non-intervention Mean (SD)	(4) Difference 1-2	1-3	2-3
Northern region	0.340	0.450	0.610	-0.110**	-0.270**	-0.160**
	(0.476)	(0.499)	(0.489)			
Upper East region	0.390	0.090	0.070	0.300**	0.320**	0.020**
	(0.488)	(0.284)	(0.261)			
Upper West region	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	216.168**	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			

Note: Standard deviations in parentheses. p<0.1, **p<0.05, ***p<0.01. The Mann-Whitney test and the Chi-square test were used for the continuous and binary variables, respectively

$$Y = DY_1 + (1 - D)Y_0 \quad (1)$$

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 (e.g. gender of household head, age, ability to read and write). For the purpose of examining the policy implication of this intervention, we estimate the average treatment effect on the treated (ATT) under the assumption of selection on observables as:

$$\mathbb{E}[Y_1 - Y_0|D = 1] = \mathbb{E}[Y_1|D = 1] - \mathbb{E}[Y_0|D = 1] \quad (2)$$

However, since famers' decision to be induced could be affected by unobserved factors (e.g. technical and managerial skills), we employ an instrumental variable (IV) regression approach in estimating the ATT. That is, we estimate the ATT under assumption of selection on unobservable. Generally, the IV exploits the variation from an instrument, Z to indirectly shift D, holding X fixed. If the instrument Z, is exogeneous, then Y is due to D (Mogstad and Torgovitsky, 2018).

Specifically, under the assumption of selection on observables, we adopt the propensity score or the kernel matching (Caliendo and Kopeinig, 2008) and the inverse propensity score weighting (IPW) method with a machine learning approach (i.e. the least absolute shrinkage and selection operator (Lasso)) in estimating the ATT. The IPW-Lasso estimates the ATT by combining both regression and propensity score weighting method together. The estimator is considered as a doubly robust method (Belloni et al., 2017; Imbens and Wooldridge, 2009). We note that the Lasso helps select the appropriate covariates for the estimation (Belloni et al. 2014a,2014b). In contrast, under the assumption of selection on unobservable, we adopt the marginal treatment effect (MTE) approach of Mogstad and Torgovitsky (2018) in estimating the ATT. We note that the MTE estimates ATT under the assumption that the treatment effect and farmers' unobserved factors vary across the farm households.

2.4.3. Heterogeneous treatment effects

Although the average treatment effect is interesting in determining effects of the inducement on farmers' maize yields and net incomes, it fails to unravel the heterogeneous treatment effects of the inducement across the farm households. Moreover, policy-makers 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. We adopt the instrumental variable quantile treatment framework due to Chernozhukov and Hansen (2005) in exploring the heterogeneous treatment effects of inducement on maize yield and net income of farmers. We estimate the τth 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 (e.g. technical skill) can affect the decision to adopt SI practices, we adopt the instrumental variable quantile regression via the control function method in estimating Y_d. We estimate Y_d using the control function approach of the IVQR due to Lee (2007).

2.4.4. 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 the programme. We follow Di Falco et al. (2011) and Di Falco and Veronesi (2013) by using information sources (e.g. 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 past effects of the inducement on maize yield and net of income past induced farmers. It is expected that farmers' access to information from extension services or groups (e.g. farmer-based organisation) about the SI practices should influence farmers' decision to continue to adopt or to be induced. On the other hand, we do not expect the information sources to affect the outcome variables directly 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 (e.g. Abdulai 2016; Bellon et al. 2020; Kassie et al. 2015; Khonje et al. 2018; Michler and Josephson 2017) by using the time taken to reach the nearest weekly market or a motorable road to proxy farmers ease and distance to reach the nearest market as instruments. It is expected that the closer and easier for farmers to interact with market forces would influence their decision to continue to adopt the SI practices. We expect that the time taken to reach the nearest weekly market or a motorable road would affect farmers' decision to be induced or adopt. On the other hand, we do not expect the time taken to reach the nearest weekly market or a motorable road to 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 or adopt but not the outcome variables (Table 2.5 A2 and 2.6 A3). Furthermore, 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 2.7 A4).

2.4.5. Cost effectiveness of the conditional inducement

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

2.5. Results

2.5.1. Mean treatment effects

First, we first explore the unconditional treatment effects of the inducement on maize yield and net income by using the density distribution curve. Figure 2.2 A1 plots the density curves of maize yield and net income of farmers by treatment type. The figure suggests a shift in the distribution of maize yield and net income of farmers in the continued and phased-out communities, indicating a positive effect of inducement on maize yield and net income of farmers.

Next, Tables 2.2-2.3 present the mean treatment effects of the inducement on maize yield and net income by treatment type. The tables present the results of three estimators' estimates of the average treatment effect on treated (ATT) under different estimation assumptions. We note that the MTE estimates control for selection on observables and unobservable, while the IPW-Lasso and the kernel matching estimates control for selection on observables.

Table 2.2: 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	

Note: *p<0.1, **p<0.05, ***p<0.01. 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 1.1-1.5 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. The inverse propensity score weighting with lasso regression (IPW-Lasso) and the kernel matching account for heterogeneity in treatment effect only.

Table 2.2 reports the mean effect of inducement for continued versus non-intervention and phased-out versus non-intervention, respectively. Overall, the estimates from the estimators are qualitatively similar under each treatment type. More specifically, the MTE estimates indicate that the continuous inducement increases the maize yield and net income of farmers in the continued community by about 32% and 36%, respectively. Whereas the estimates reveal that past inducement still increased maize yield and net income of past induced farmers by about 10% and 0.4%, respectively albeit not significant. In summary, table 2.2 indicates persistence learning and inducement effects on maize yield and net income of farmers in the continued communities. The table also indicates that the past inducement effects can still be observed on maize yield and net income of past induced farmers, even though the estimates are not statistically significantly different from zero.

2.5.2. The gains or losses with continuation of the inducement

Table 2.3 presents the mean inducement effect on maize yield and net income of farmers for continued versus phased-out communities. Overall, the table implies a positive and significant effect of continuous inducement on maize yield and net income of farmers in the continued communities. Specifically, the MTE estimates imply that the continuous inducement increased maize yield and net income of the continuous induced farmers by approximately 64% and 53%, respectively. This result suggests persistence learning and inducement effects among farmers in the continued communities.

Table 2.3: Mean effect of inducement on maize yield and net income

Estimator	Continued vs Phased-out	
	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	

Note: *p<0.1, **p<0.05, ***p<0.01. 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 1.1-1.7. 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. The inverse propensity score weighting with lasso regression (IPW-Lasso) and the kernel matching account for heterogeneity in treatment effect only.

2.5.3. Heterogeneous treatment effects

Although the mean effects in tables 2.2 and 2.3 present positive effects of the inducement, they failed to indicate the distributional effects of the inducement on maize yield and net income of farmers, and thus we explore the effects. Figure 2.1 plots the 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. The point and vertical lines denote point estimate and the 90% confidence intervals, respectively.

Overall, the quantile estimates imply that the distributional effects of the inducement on maize yield and net income of farmers vary across the quantile indexes. More specifically, 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 the maize yield and below quantile 30 and above quantile 70 for the net income.

Furthermore, the middle panel suggests positive effects of past inducement on maize yield and net income below quantile 30 for maize yield and net income, respectively. Specifically, we find significant effect of past inducement on maize yield and net income of farmers below quantile 20. This result suggests that farmers at the lower quantile indexes still benefits 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 and significant effects of continuous inducement on maize yield and net income of farmers across the quantile indexes, especially at the bottom quantile indexes, indicating that continuous induced farmers at these quantile indexes benefited greatly from the continuous inducement.

2.5.4. Is the inducement cost effective?

We calculated the cost effectiveness of the conditional inducement *vis-a-vis* organising a farmer field day to spur farmers' adoption of SI practices. We used the average net income of maize yield derived by an induced and an uninduced farmer from a continued community to calculate the cost and benefit of inducing 30 farmers through a conditional inducement and a farmer field day, respectively. Tables 2.8 A5 and 2.9 A6 present the cost and benefit analysis for the two scenarios. Table 2.8 A5 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 2.9 A6). In summary, the two tables suggest that the conditional inducement is somewhat more cost effective than a farmer field day.

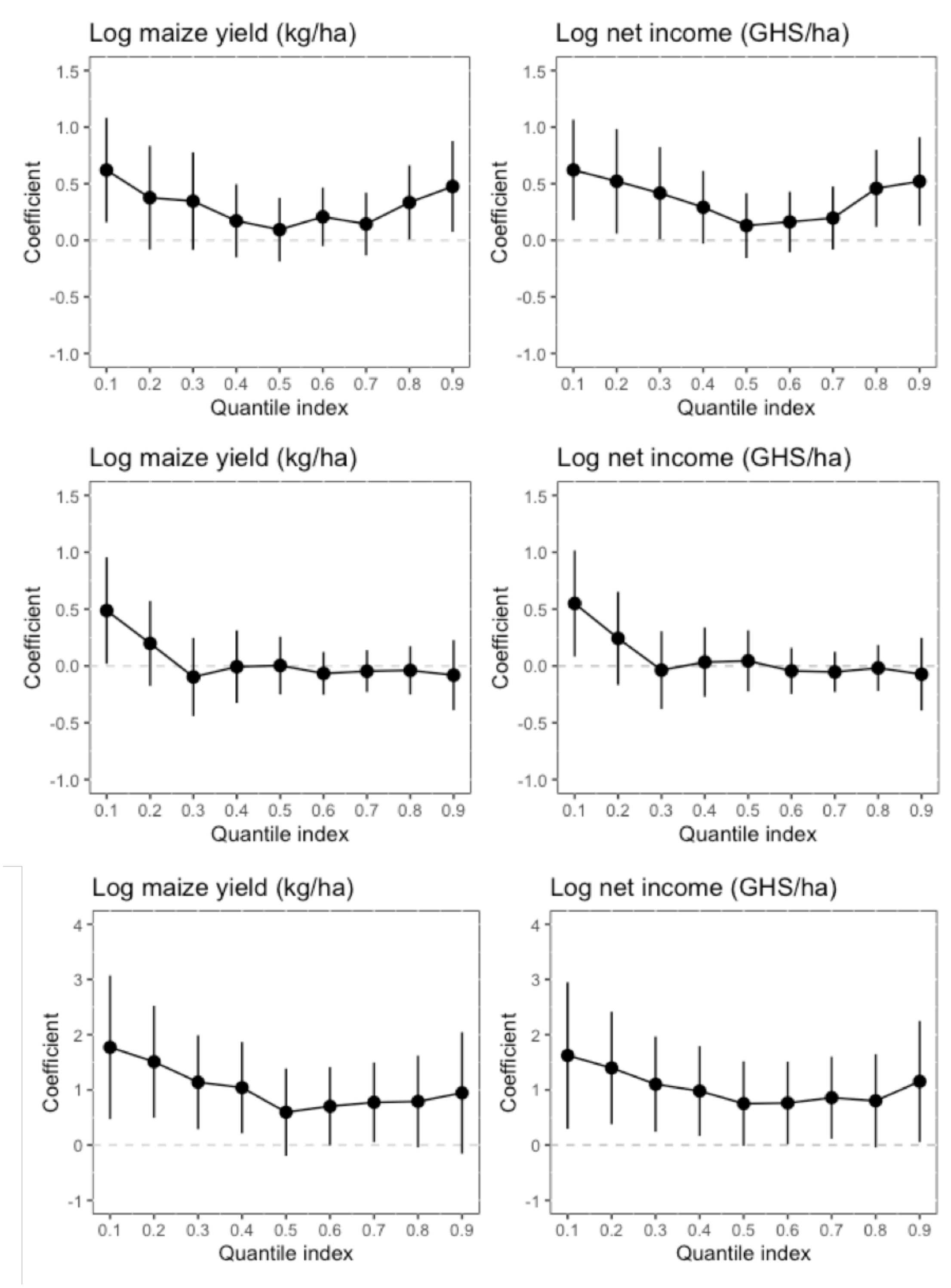

Figure 2.1: Distributional effects of conditional inducement on maize yield and net income of farmers for continued versus non-intervention (top panel), phased-out versus non-intervention (middle panel), and continued versus phased-out (bottom panel), respectively. The point and the vertical lines represent the point estimates and the 90% confidence intervals, whereas the grey line from zero denotes our reference line and it helps evaluate the differences of the quantile effects from zero.

2.6. Discussion and conclusion

Stimulating adoption of agricultural innovations among smallholder farmers in SSA is essential towards reducing food and nutrition insecurity and enhancement of crop and soil productivity. This study examines the conditional inducement of farmers to adopt sustainable intensification of agricultural practices (SI practices) and its effect on maize yield and net income of farmers. We examine the effects of the inducement by contrasting induced farmers with non-induced and past induced farmers.

Our result revealed that the adoption of SI practices increased maize yield and net income of farmers. This finding agrees with studies (e.g. Kim et al., 2019; Kotu et al., 2017) that showed positive effect of adopting SI practices on crop productivity and farm income. Furthermore, our finding implies that the inducement led to an increase in maize yield and net income of farmers. This result corroborates with the results of other studies (e.g. Carter et al., 2016; Omotilewa et al., 2019) that showed that the adoption of agricultural technologies among smallholder farmers can be stimulated via inducement (e.g. subsidy, payment of ecosystem services).

Furthermore, our findings suggested that the continuous inducement of farmers led to significant increases in maize yield and net income of farmers, whereas the termination led to positive but insignificant effect on maize yield and net income of past induced farmers. These results highlight the importance of persistence of inducement and enhancement of farmers' human capital via training and testing of agricultural technologies by farmers, especially during diffusion of new agricultural technologies. Moreover, our observed heterogeneous effects of inducement on maize yield and net income of farmers across the quantile indexes indicated variability in the learning and inducement effects across the farm households.

The distributional effects of positive and significant effects of past inducement on maize yield and net income of farmers at the bottom of the quantile indexes compared to those from the middle to the top quantile indexes indicated that the termination or withdrawal effects of the inducement vary across the farm households. In other words, some farmers are more likely to experience greater negative effect from abrupt withdrawal or termination of intervention than others, particularly in interventions that stimulate farmers' adoption of agricultural technologies and practices. This may be due to differences in farmers' resource endowment(Giller et al., 2011).

The findings of this study have important implications for technology adoption and inducement of farmers to adopt new agricultural technologies. First the results indicate that conditioning of incentives (e.g. fertiliser subsidy programme) can be used to stimulate farmers' adoption of new agricultural technologies. Second, the findings reveal that crop productivity and farm incomes of smallholder farmers can be enhanced via the diffusion of SI practices. Third, the results suggest targeting of inducement and its withdrawal rather than adopting a broad-based approach when inducing farmers to adopt agricultural technologies. Fourth, the results show that persistence of intervention matters, especially in intervention that involve gaining experience and learning. Finally, the findings indicate that agricultural programmes and policies that aimed at stimulating farmers adoption of new agricultural technologies should not only focus on overcoming the immediate obstacles to adoption through the provision of inputs, but rather should also aim at sustaining adoption (Maggio et al., 2021). This would require provision of support services (e.g. constant improvement of farmers' human capital via extension services) and the conditioning of existing programmes (e.g. social protection programmes) to the adoption of sustainable agricultural practices. This would demand the involvement of relevant government ministries (e.g. social welfare, agriculture) in the diffusion of agriculture technologies process.

Appendix 2

Table 2.4 A1: Descriptive statistics

Variable	Description	Mean (SD)
Female	Gender of household head(1=female,0=otherwise)	0.260 (0.439)
Age	Age of household head in years	47.600 (14.047)
Dependency ratio	Number of non-active members under 15 and above 65 divided by members between 15-64	1.094 (0.711)
Read and write	Household head can read and write (1=yes, 0=otherwise)	0.150 (0.360)
Household size	Total number of household member	8.780 (4.927)
Group membership	Household member belong to a CBO or an FBO (1=yes, 0=otherwise)	0.180 (0.387)
Extension services	Received advise from an extension agent or NGO (1=yes, 0=otherwise)	0.620 (0.485)
Farm size	Total crop area in hectare (ha)	1.416 (1.634)
Livestock holding	Total livestock in Tropical Live Unit (TLU)	3.482 (6.942)
Off-farm income	Non-agricultural income in Ghana cedis (GHS) per month	142.684 (296.002)
Productive assets	Total number of durable assets	8.220 (6.270)
Market	Minutes taken to reach the nearest weekly market	31.913 (25.324)
Motorable road	Minutes taken to reach the nearest motorable road	6.065 (10.846)
Northern region	Household lives in the Northern region (1=yes, 0=otherwise)	0.480 (0.500)
Upper West region	Household lives in the Upper West region (1=yes, 0=otherwise)	0.350 (0.476)
Upper East region	Household lives in the Upper East region (1=yes, 0=otherwise)	0.170 (0.378)
Maize yield	Average maize yield in kilogram per hectare (kg/ha)	1075.193 (684.372)
Net income	Average net income in Ghana cedis per hectare (GHS/ha)	809.006 (2836.819)
Observations		700

Note: Standard deviations are in parentheses.

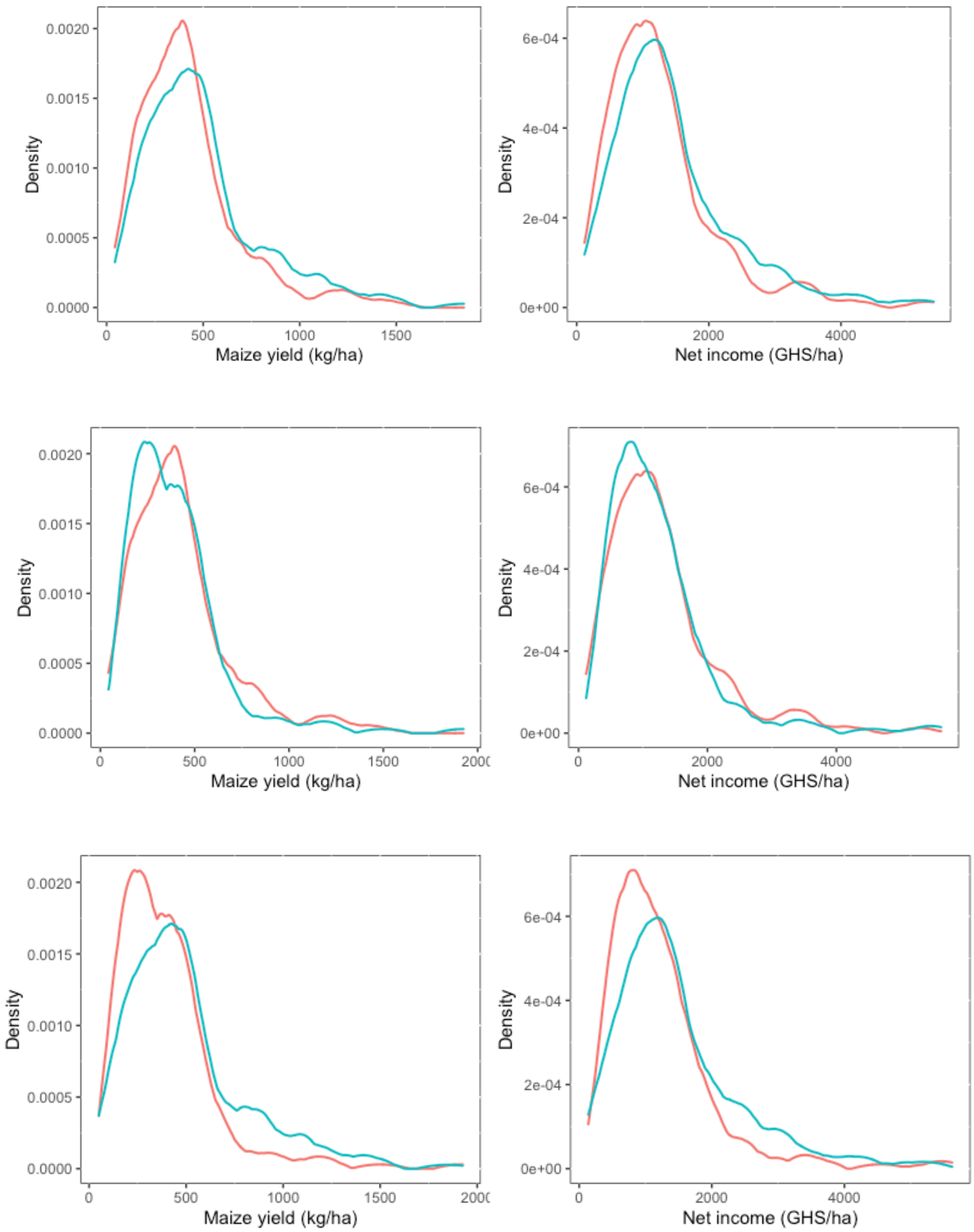

Figure 2.2 A1: Kernel density curves of maize yield and net income of farmers for continued versus non-intervention (top panel), phased-out versus non-intervention (middle panel), and continued versus phased-out (bottom panel). The red curve denotes non-intervention or phased-out maize yield or net income of farmers, whereas the green curve denotes maize yield and net income of farmers in either continued or phased-out communities.

Table 2.5 A2: Test of instrument validity for continued versus non-intervention

Variable	Decision to be induced (1/0)	Log maize yield (kg/ha)	Log net income (GH/ha)
Extension agent or NGO	2.530***(0.311)	0.102(0.085)	0.115(0.086)
Group	0.234(0.212)	0.178(0.140)	0.198(0.141)
Constant	-2.097(0.605)	7.274*** (0.246)	7.635*** (0.249)
Wald test	χ^2=285.55***	F(2,255)= 1.53, p=0.218	F(2,255)= 1.55, p= 0.214
R^2	0.483	0.049	
Observations	443	271	

Note: *p<0.1, **p<0.05, ***p<0.01. Standard error in parentheses Estimates for the maize yield and net income were obtained with the ordinary least squares (OLS) method. For brevity, we did not report all the parameters.

Table 2.6 A3: Test of instrument validity for phased-out versus non-intervention

Variable	Decision to be induced (1/0)	Log maize yield (kg/ha)	Log net income (GH/ha)
Extension agent or NGO	3.287*** (0.441)	0.102(0.085)	0.115(0.086)
Group	0.082(0.214)	0.178(0.140)	0.198(0.141)
Constant	-3.061***(0.652)	7.274*** (0.246)	7.635*** (0.249)
Wald test	χ^2=264.30***	F(2,255)= 1.53, p=0.218	F(2,255)= 1.55, p= 0.214
R^2	0.45	0.049	0.068
Observations	440	271	

Note: *p<0.1, **p<0.05, ***p<0.01. Standard error in parentheses. Estimates for the maize yield and net income were obtained with the ordinary least squares (OLS) method. For brevity, we did not report all the parameters.

Table 2.7 A4: Test of instrument validity for continued versus phased-out

Variable	Decision to be induced (1/0)	Log maize yield (kg/ha)	Log net income (GH/ha)
Distance to the nearest market	-0.931***(0.230)	-0.226 (0.137)	-0.212(0.139)
Distance to the nearest motorable road	9.386**(0.191)	0.121(0.116)	0.122(0.118)
Constant	2.015** (0.936)	7.482***(0.673)	7.800***(0.684)
Wald test	χ^2=17.300***	F(2,153) = 1.94, p= 0.147	F(2,153) = 1.39, p= 0.251
R^2	0.20	0.083	0.092
Observations	341	169	

Note: *p<0.1, **p<0.05, ***p<0.01. Standard error in parentheses. Estimates for the maize yield and net income were obtained with the ordinary least squares (OLS) method. For brevity, we did not report all the parameters.

Table 2.8 A5: Cost-benefit analysis of inducement per season in a community

			Value
Benefits			
	1	Average net income of maize yield of an induced farmer (GHS/ha)	1481.744
	2	Average number of induced farmers per community	30
	3	Expected benefit (GHS) (1*2)	44,452.32
Costs			
	4	Cost of incentives per farmer (maize seeds plus fertilisers)	250
	5	Number of farmers per village	30
	6	Total cost of incentive per village (4*5)	7500
	7	Cost of training farmers at the technology park	500
	8	Total cost per village (6+7)	8000
Net benefit per village in a season (3-8) (GHS)			36452.32
Benefit-cost ratio (3/8) per season			5.56

Note: 1 USD= 5.4 GHS at the time of the survey. The average maize yield of an induced farmer is about 1242 kg/ha in a continued community.

Table 2.9 A6: Cost-benefit analysis of farmer field day per season in a community

			Value
Benefits			
	1	Average net income of maize yield of an uninduced farmer in a community (GHS/ha)	1186.660
	2	Expected average number of farmers at a farmer field day	30
	3	Expected benefit (GHS) (1*2)	35599.8
Costs			
	4	Administrative cost of organizing a farmer field day per village	6000
	5	Average number of farmers and other stakeholders expected at a field day‡	40
	6	Time cost per attendance (GHS)	33
	7	Total time cost for farmers and other stakeholders per village (5*6)	1320
	8	Total cost per village (4+7) (GHS)	7320
Net benefit per village in a season (3-8) (GHS)			28,279.8
Benefit-cost ratio (3/8) per season			4.86

Note: 1 USD= 5.4 GHS at the time of the survey. The average maize yield of an uninduced farmer in a continued community is about 998.7237 kg/ha. ‡This includes opinion leaders and staff from the ministry of agriculture. We note that the estimates are from the 40 uninduced farmers who participated in the farmer field day in the continued communities.

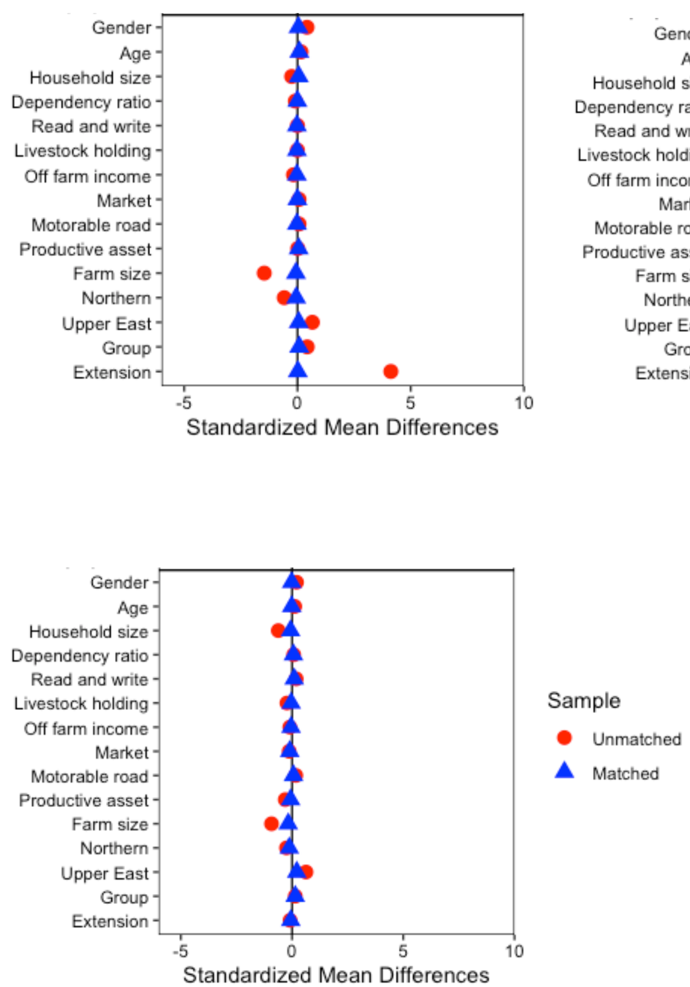

Figure 2.3 A2: Covariate balance for continued versus non-intervention (top left), phased-out versus non-intervention (top right), and continued versus phased-out (bottom left) for the kernel matching estimation.

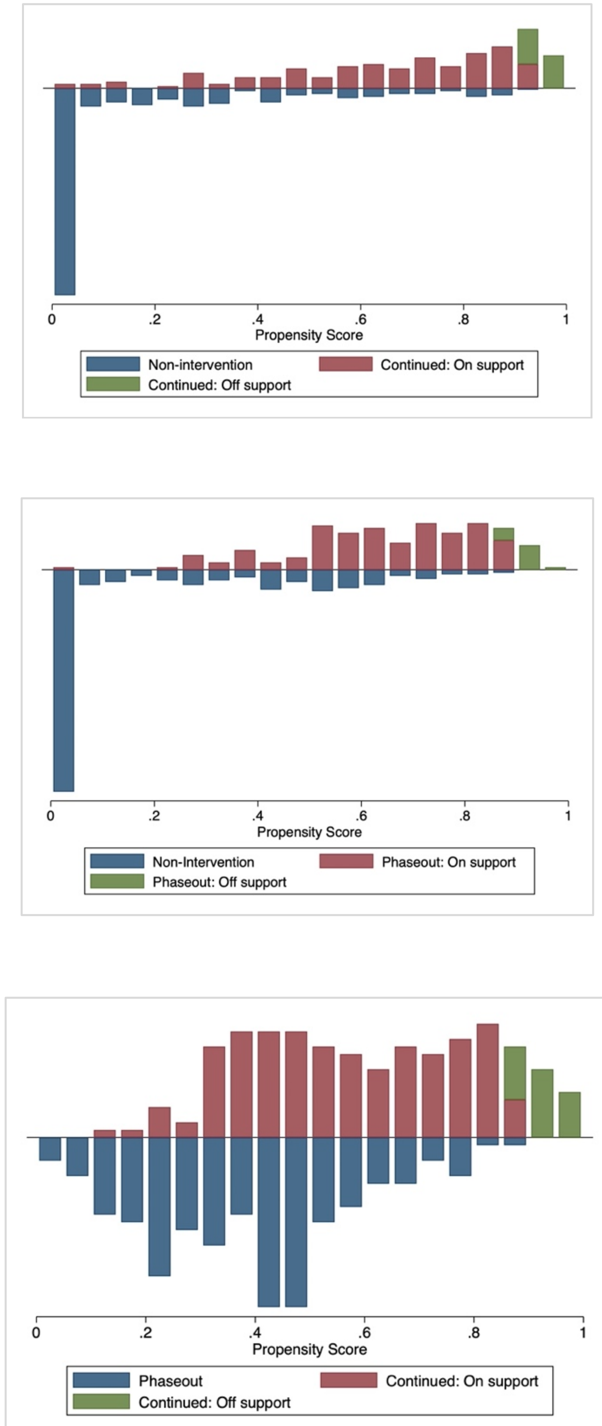

Figure 2.4 A3: Propensity score distribution showing region of common support between farmers in continued versus non-intervention (top panel), phased-out versus non-intervention (middle panel), and continued versus phased-out (bottom panel) for the kernel matching estimation.

Chapter 3: Scaling-up agricultural technologies: Who should be targeted?[+]

Abstract

The effects of adopting new agricultural technologies 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 endowments 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.

[+] The essay is co-authored by Carlo Azzarri, Bekele Hundie Kotu, Lukas Kornher and Joachim von Braun. I conceptualized the research, collected the data, developed the methodology, carried out the formal analysis, and wrote the manuscript. Carlo Azzarri, Bekele Hundie Kotu, Lukas Kornher and Joachim von Braun supervised the research, commented and edited the manuscript. A version of the essay has been published in the European Review of Agricultural Economics under the same title.
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3.1. Introduction

Adoption of new agricultural technologies bears profound implications on farm structure and organisation, being strongly linked to increasing crop productivity and farm income, as well as reducing poverty. Especially over the last three decades, several agricultural technologies have been disseminated across sub-Saharan Africa (SSA). Nevertheless, their adoption rates among farm households have historically been very poor, although a large body of empirical evidence has shown that these agricultural technologies bear positive outcomes (Giller et al., 2009; Moser and Barrett 2003; Grabowski et al., 2016 among others).

Literature has identified lack of information (Ashraf et al., 2009), poor road network (Karlan et al., 2014), inadequate use of inorganic fertiliser (Duflo et al., 2011), lack of access to new inputs (Emerick and Dar 2021), and differences in agroecological conditions (Giller et al., 2009; Giller et al., 2011) as some of the causes for the poor adoption. Less documented are the scaling up methods and the types of marginal farm household entrants (that is, farm households who are indifferent as to whether to adopt or dis-adopt a specific technology) that need to be targeted during scaling up. Technology targeting can greatly affect farm-based livelihoods given the heterogeneity of farming systems in SSA according to resource endowment and agroecological conditions that lead to differential farmer responses to interventions (Giller et al., 2009; Giller et al., 2011). Failure to consider this heterogeneity during scaling up of agricultural technologies can substantially affect farmers' decision to adopt. Moreover, leakage and mistargeting during scaling up pose serious concerns under scarce financial and human resources.

The literature on technology adoption in SSA is largely focused on average effects (e.g.Kotu et al. 2017; Khonje et al. 2018) with a limited number of studies on the heterogeneous effects (e.g. Michler et. al, 2019; Abdul Mumin and Abdulai 2021). However, the average effect barely contributes to policy decisions affecting scale-up (Heckman and Vytlacil, 2005; Mogstad and Torgovitsky, 2018) or predicting the marginal farm entrants to be targeted during scaling up.

As part of testing and dissemination of sustainable intensification (SI) practices in northern Ghana, we explore the heterogeneous effects of farmers' resource endowment and unobserved factors 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. To achieve these objectives, we frame the study within the context of an agricultural research for development programme in northern Ghana, where SI practices have been demonstrated to farmers using various channels and delivery mechanisms. These practices have been identified and tested as suitable in the heterogeneous farming systems in northern Ghana.

The empirical approach of the current study relies on the use of the marginal treatment effect (MTE) approach appeared in the recent literature (e.g. Abdul Mumin and Abdulai 2021; Shahzad and Abdulai 2020) in assessing the heterogeneous treatment effects of agricultural technology adoption on crop yields and household welfare. However, the conditional MTE approach adopted in previous studies has several limitations: a) it restricts the evaluation of different expansionary policy effects among marginal entrants and; b) it relies strongly on the variation of treatment effects across unobserved or latent resistance to adopt agricultural technologies. In contrast, we employ the unconditional MTE approach proposed by Zhou and Xie (2018, 2019) which relies on the variation of treatment effects across both observed and unobserved factors simultaneously. The newly defined MTE can be used to predict several policy effects compared to the old or the conditional MTE. In addition, as a robustness check, we validate the findings of the unconditional MTE with the instrumental variable quantile parameter estimates that point towards specific household types as benefiting the most when SI practices are scaled up and -out.

The current study contributes to the literature as follows. First, we show that both farmers' resource endowment and unobserved factors (e.g., innate ability or managerial skills) influence the marginal benefits of agricultural technology adoption, with the effects highly heterogeneous across farm households. We posit that this contribution is specifically important for agricultural policy in SSA given the farming systems heterogeneity in the region in terms of farmers' resource endowment and agroecological conditions (Giller et al., 2009; Giller et al., 2011). Second, we contribute to the literature by not only estimating the heterogeneous effects of agricultural technology adoption and practices on crop yields and net returns, but also predicting the types of 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.

Our findings have several implications. First, they suggest that adoption of SI practices increase both maize yield and net returns of maize and legume production among adopters. Second, they show that both farmers' resource endowment and unobserved factors affect the marginal benefit of adopting SI practices. Third, they reveal that the average benefits of treated farm households are greater than the average marginal benefits among the marginal farm household entrants. Finally, our scaling up policy analysis indicates that enhancing 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 3.2 discusses the study context. Sections 3.3 presents the conceptual model and the empirical strategy. Section 3.4 presents the results and discussion, and Section 3.5 discusses the conclusions and policy implications.

3.2. Study context

3.2.1. Background

The Africa RISING 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 crop-livestock farming systems via demonstration and dissemination of improved agricultural technologies and practices.

To improve the cereal-legume based farming systems of farmers across northern Ghana, several new agricultural technologies and practices were demonstrated to farmers through the use of a technology park, which serves as a learning and dissemination centre. The technology park was sited across all the project intervention zones. Examples of the new agricultural technologies and practices demonstrated included efficient fertiliser application, use of improved seed varieties, cereal-legume intercropping, different crop spacing, and line sowing.

Prior to the start of the programme, the administrative districts of the then three northern regions were stratified into six main domains based on agroecological potentials of the regions and market access. Fifty communities were sampled across the domains. That is, 25 communities were purposely sampled, and received intervention from the programme, whereas the rest of the 25 communities, randomly sampled, did not received any intervention (Guo and Azzarri, 2013; Tinonin et al., 2016). We termed these communities as non-intervention communities. In 2016, the programme stopped its activity in 13 intervention communities due to lack of funds from the major sponsor. Thus, in this study we consider adopters of SI practices as farmers who have adopted or applied two or more of the SI practices on their plots for more than one cropping season after 2015. This is to capture the intensity of application of the SI practices by farmers in both the continued and dropped out intervention communities.

3.2.2. Study area

Northern Ghana is classified under the savannah agroecological zone, characterised by one growing season. Farm households in the regions cultivate cereals (e.g. maize, rice), legumes (e.g. cowpea, soybean), root and tuber crops (e.g. yam), and vegetables (e.g. cabbages). Majority of these crops are produced under rain fed agriculture. Some farm households also raise small (e.g. sheep and goat) and large ruminants (e.g. cattle), poultry, and pigs. Nevertheless, the poverty levels among the majority of farm households across the regions are the highest in the country (MoFA, 2017).

3.2.3. Data

The current study is a follow-up of the Ghana Africa-RISING Baseline Survey conducted in 2014 where 1248 farm households across the intervention and non-intervention 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, a power analysis was conducted to estimate the total sampled size required for an impact analysis. 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, we sampled 428 households from the intervention communities, and 271 farm households from the control communities.

Using the same baseline questionnaire, a team of trained research assistants conducted face-to-face interviews with the sampled farm households across the regions. Information elicited from farmers ranged from socio-economic characteristics of the households, crop production, storage, to food and nutrition security.

3.2.4. 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 (for example, gender, age, educational background), dependency ratio, household size, farm size, number of livestock, access to extension services, group membership, number of productive assets, off-farm income, the time taken reach the nearest market or motorable road, and agroecological zones. We expect the latter variable to pick up rainfall patterns, as well as the farming systems across the agroecological zones. For example, farmers in the Sudan savannah zone plant on ridges due to low soil depth compared with those in the Guinea savannah zone, where most farmers plant on the soil surface. In addition, the mean annual rainfall for the Guinea savannah (1100mm) is generally higher than that of the Sudan savannah (900-1000mm)(MoFA, 2017).

We selected our outcome variables based on the programme goals. We focused on maize yield and net returns. 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 3.1 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 men, and the average age of a given household head is around 48 years. About 85% of the household head cannot read and write, and most farmers source their agricultural information from extension agents or NGO's. The table also indicates that the average farm size and herd size for a given household are 1.44 ha and 3.4 TLU, respectively. In 2013, a given household harvested an average maize yield of about 961 kg/ha compared to around 1081 kg/ha in 2018. In addition, the average net returns for the maize and legume yields is about 367 GHS/ha in 2013 compared to around 826 GHS/ha in 2018.

Furthermore, Table 3.5A1 reports the mean differences between covariates of the adopters and the non-adopters of the SI practices and their P-values. The table implies a significance difference for the covariates gender, group membership, access to information from extension agents or NGO's, farm size, information from friends, agroecological zones, and net returns in 2018. This finding indicates that a simple mean difference between the outcome variables of adopters and non-adopters cannot be attributed to the effect of adopting SI practices since the estimate will be biased upward.

Table 3.1: 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 hectare (ha)	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	

Note: 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 or dissimilar farm households from the dataset.

3.3. Conceptual framework and empirical strategy

3.3.1. Conceptual framework

Following Abdulai and Huffman (2014), we assume that farmers are risk neutral and will adopt the SI practices if the net benefit is greater than alternative practices. That is, suppose Y_1 is the returns from adopting SI practices and Y_0 is the returns from non-adoption, then farmers will adopt the SI practices if $Y_1 > Y_0$ (Pitt 1983). It is worth noting that the farming systems in SSA are very heterogeneous in terms of resource endowment and agroecological conditions, and thus the returns from adopting SI practices will vary across farm households. In addition, some farmers may be able to forecast the future gains in adopting SI practices at early stage due to unobserved factors such as managerial and technical skills. The differences in returns among farm households or farmers and the ability of farmers to forecast future benefits suggest that the average benefit of adopting SI practices may differ from the marginal benefit for new farmers at the margin of adoptions.

3.3.2. Empirical strategy

To capture both treatment effect heterogeneity and unobserved factors in our estimation, we adopt the redefined marginal treatment (MTE) framework. For purpose of clarity, we present the marginal treatment effect concept first proposed by Björklund and Moffitt (1987) and later developed by Heckman et al. (2005) as a tool for policy analysis. We follow this with the redefined or unconditional marginal treatment effects framework proposed by Zhou and Xie (2019, 2018). Finally, we contrast the old and the redefined marginal policy relevant treatment effect proposed by Carneiro et al. (2010) and Zhou and Xie (2019, 2018), respectively, for predicting the effect of a given policy.

3.3.3. Overview of the old marginal treatment effect framework

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

$$Y_0 = \mu_O(X) + \varepsilon \quad (1)$$

$$Y_1 = \mu_1(X) + \varepsilon + \rho, \quad (2)$$

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

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

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

$$I_D = \mu_D(Z) - V \quad (4)$$

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

where $\mu_D(Z)$ is unknow function, V is a latent random variable that captures unobserved factors, and Z denotes a vector that captures the pre-treatment covariates X and includes instrumental variables that influence the treatment D. The key assumptions underlining the latent index model are 1) ε, ρ, V are independent of Z given X, and 2) $\mu_D(Z)$ is a nontrivial function of Z given X. These assumptions indicate that the assignment to treatment can be rewritten as:

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

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 Z affects the treatment status via the propensity score $P(Z)$.

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

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

They show that causal estimands such the average treatment effect ATE, the treatment effect on the treated (TT) and the treatment effect on the untreated (TUT) can be expressed as the weighted averages of the $MTE(x,u)$ (Heckman et al. 2005).

3.3.4. The newly defined marginal treatment effect 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 in fact means that the entire treatment effect heterogeneity that is important for selection bias to exit can be expressed as a function of a) the propensity score $P(Z)$, and b) the latent variable or resistance to adopt U. This means that a person is only treated if her propensity score exceeds her latent resistance to adopt. Given $P(Z)$ and U, the treatment effect status D is fixed and is independent of the treatment effect. This 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 independent. 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 or adopt U or u. That is

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

The advantages the newly defined $\widetilde{MTE}(p,u)$ has over the old $MTE(x,u)$ are: 1) it is simply a bivariate function that captures treatment effect heterogeneity in a more parsimonious way, 2) it is very easy to be visualized, and 3) 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 like the old $MTE(x,u)$, causal estimands such as the ATE(p), TT(p) and TUT(p) can be estimated using the appropriate weight from the propensity score (Zhou and Xie (2019, 2018).

3.4. Overview of the old marginal policy relevant treatment effect

To predict the policy implications of a programme expansion or contraction, 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 per shift into treatment. That is

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

where W is the treatment choice that is made after 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 answering economic of interest, Carneiro et al. (2010) proposed the marginal policy relevant treatment effect ($MPRTE$) concept as the directional limit of the $PRTE$:

$$MPRTE = \lim_{\alpha \to 0} PRTE(F_\alpha). \tag{11}$$

Where $F(.)$ is the cumulative distribution function of $P(Z)$. They defined a set of alternative policies by a scalar α, where F_0 denotes the baseline policy. Their $MPRTE$ is estimated under the assumption that the policy change is via a shift in the conditional distribution of $P(Z)$ given X.

3.3.5. The newly defined marginal policy relevant treatment effect

Following the same argument of Carneiro et al. (2010), Zhou and Xie (2019, 2018) proposed a policy change that shift the conditional distribution of the $P(Z)$ directly without conditioning it on X. This captures policy change 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 $Z|X$. To explore the effect of a marginal policy change, Zhou and Xie (2019, 2018) consider 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 the α gets closer to zero. That is

$$\begin{aligned} \widetilde{MPRTE}(p) &= \lim_{\alpha \to 0} PRTE(p, \alpha\lambda(p)) \\ &= [Y_1 - Y_0 | p(Z) = p, U = p] \\ &= \widetilde{MTE}(p, p). \end{aligned} \tag{12}$$

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

3.3.6. Treatment effect heterogeneity among marginal entrants

During an expansion of an intervention such as scaling up SI practices, a key question that every policymaker would like to find out is how does the $\widetilde{MPRTE}(p)$ changes with the propensity score p (or resource endowment of households). To answer this question, we look at the components of the $\widetilde{MPRTE}(p)$. It is important to note that substituting equation (7) into equation (12) would lead to:

$$\widetilde{MPRTE}(p) = \mathbb{E}[\mu_1(X) - \mu_O(X)|P(Z) = p] + \mathbb{E}[\rho|U = p]. \quad (13)$$

We note that the first component of the equation 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 directions and thus the $p = P(Z)$ captures both treatment effects heterogeneity in observed and unobserved directions (Zhou and Xie ,2019, 2018).

The adoption literature has established the fact that farmers who are more likely to benefit from adoption are most likely to adopt. In other words, there is a negative relationship between the latent resistance to adopt U and the unobserved factor that affect treatment effect ρ, implying positive selection into treatment. Nonetheless, the adoption literature has paid less attention to the first component, which concerns whether farmers who by observed characteristics appear more or less likely to adopt also benefit from adoption.

Often times, one cannot tell whether low or highly resource endowed farm households are more or less likely to benefit from scaling up because of unobserved selection factors. However, an observation of the second component shows that a stronger negative relationship between ρ and U would cause the $\widetilde{MPRTE}(p)$ to decline with p (Zhou and Xie, 2019, 2018). In this instance, one would observe a negative selection among the farm households at the margin of adoption, indicating that households who by observed characteristics appear least likely to adopt would benefit more from adoption. However, this observed negative selection is rather due to positive selection into treatment or unobserved sorting on gain (Zhou and Xie, 2019, 2018).

Overall, the MTE framework composed of the choice and return equations. The choice equation is estimated using the 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 like the old MTE for identification, we follow Di Falco et al. (2011) by using information sources as selection instruments (e.g. extension or NGO, friends, other farmers, group membership). For a valid instrument, we expect that the information sources would influence the decision to adopt, but not the output of non-adopters. We conduct a simple falsification test to check the validity of the instruments. Our test shows that the instruments are valid and relevant (Table 3.6A2). That is, the instruments jointly influence the decision to adopt the SI practices (Model 1: χ^2=111.80 p=0.000) but not of maize yield (Model 2: F-stat.=0.299, p=0.392) and net returns of maize and legume yield (Model 3: F-stat.=1.030, p=0.879) of non-adopters.

3.4. Results and discussion

3.4.1. Decision to adopt SI practices

The first stage of the $\widetilde{MTE}$ model estimates the propensity to adopt the SI practices. We note that our first stage of the $\widetilde{MTE}$ or the choice equations for maize yield and net returns consist of all the covariates in Table 1 excluding the baseline information of each outcome variable. Figure 3.1 displays the region of common support or intersection between adopters and non-adopters using the estimated propensity score from the first stage of the $\widetilde{MTE}$. The figure indicates a good region of common support or intersection between the adopters and non-adopters.

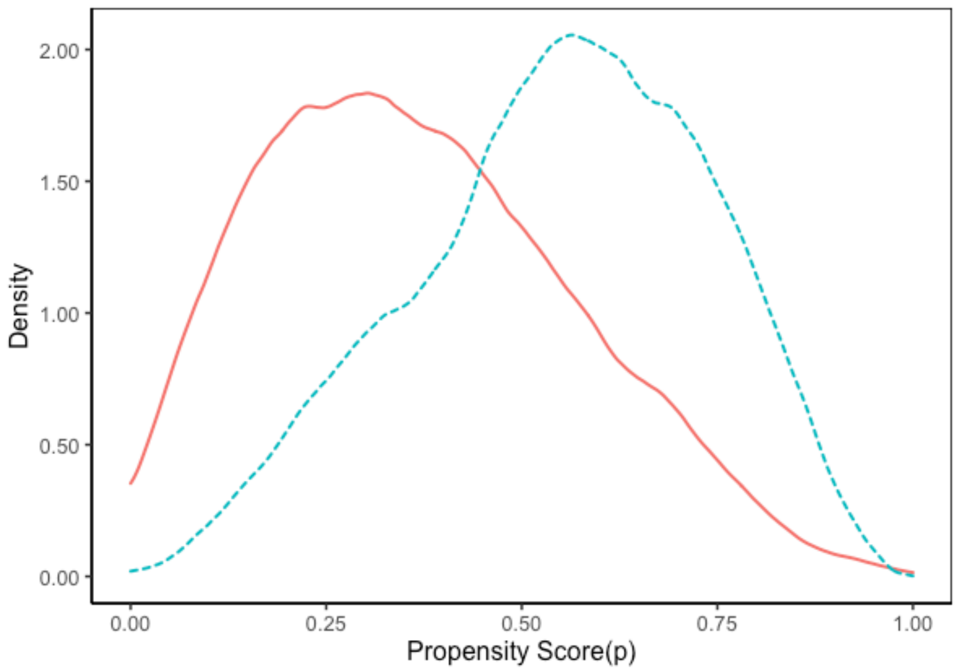

Figure 3.1: Region of intersection or common support by adoption status. Dashed and solid lines denote adopters and non-adopters, respectively. Note that the propensity score is estimated from the choice equation or the first stage of the $\widetilde{MTE}$. The covariates for the choice equation (or first stage of the $\widetilde{MTE}$) for maize yield and net returns for maize and legume yield are the same.

Table 3.2 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 such that the inability of other farmers to explain them well may deter others farmers from adopting.

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. The finding is not surprising because most farmers across the regions rely on family labour for their farming activities and tend to rely on simple implements (e.g. cutlass) for their farming operations.

Table 3. 2: Decision to adopt SI practices

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

Note: *, ** and *** denote statistical significance at 10-percent, 5-percent, and 1-percent 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.

3.4.2. Heterogeneity in the treatment effects

Figures 3.2 and 3.3 illustrate the treatment effect heterogeneity based on the $\widetilde{MTE}(p, u)$ and the $MPRTE(p)$ for farmers at the margin of adoption, respectively for maize yield and net returns of maize and legume yield. They present the propensity score p and the latent resistance to adopt U, ranging from 0 to 1. The shaded regions show the treatment effect heterogeneity. This is divided into 10 grids, which leads to a total of 100 grids. The grids, for example, provide a meaningful representation of the treatment effect heterogeneity for the subpopulation of the treatment effect on the treated (TT) and treatment effect on the untreated (TUT) as depicted in Figures 3.7A1 and 3.8A2, respectively. For all the graphical representations, darker shaded regions denote higher treatment effect.

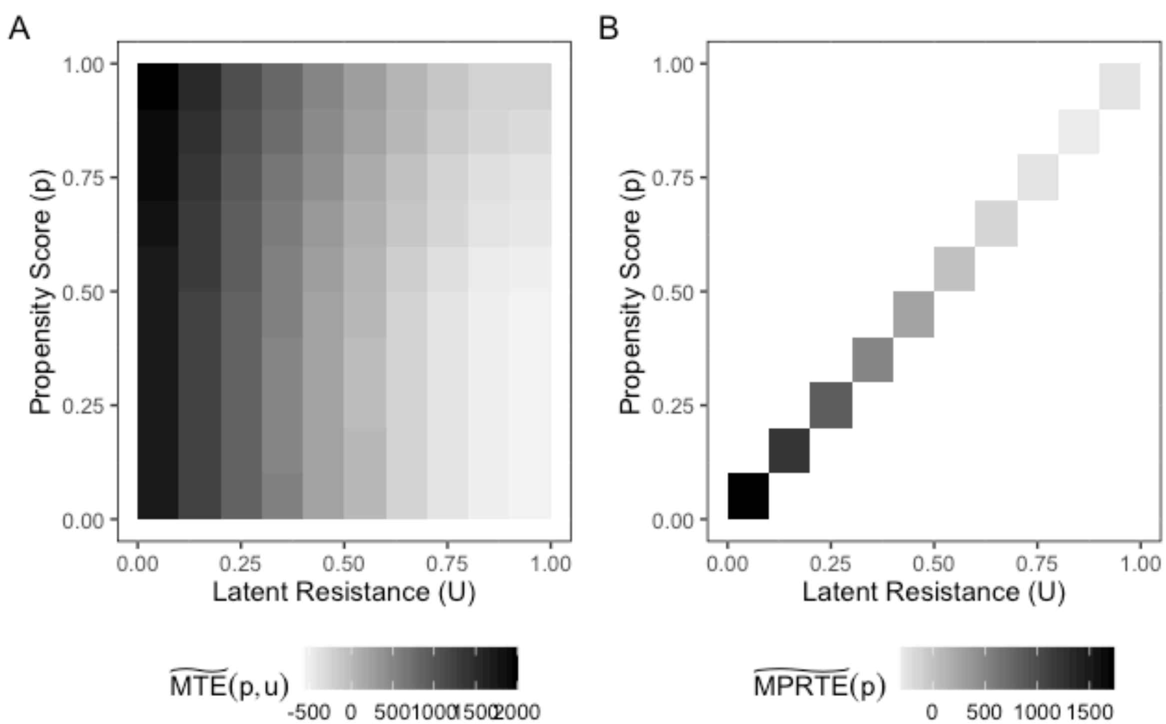

Figure 3.2: Treatment effect heterogeneity based on $\widetilde{MTE}(p, u)$ and $\widetilde{MPRTE}(p)$ for maize yield (kg/ha). Note that the darker the colour the higher the treatment effect. Also, the trends for the maize yield only is similar to the net returns of maize yield.

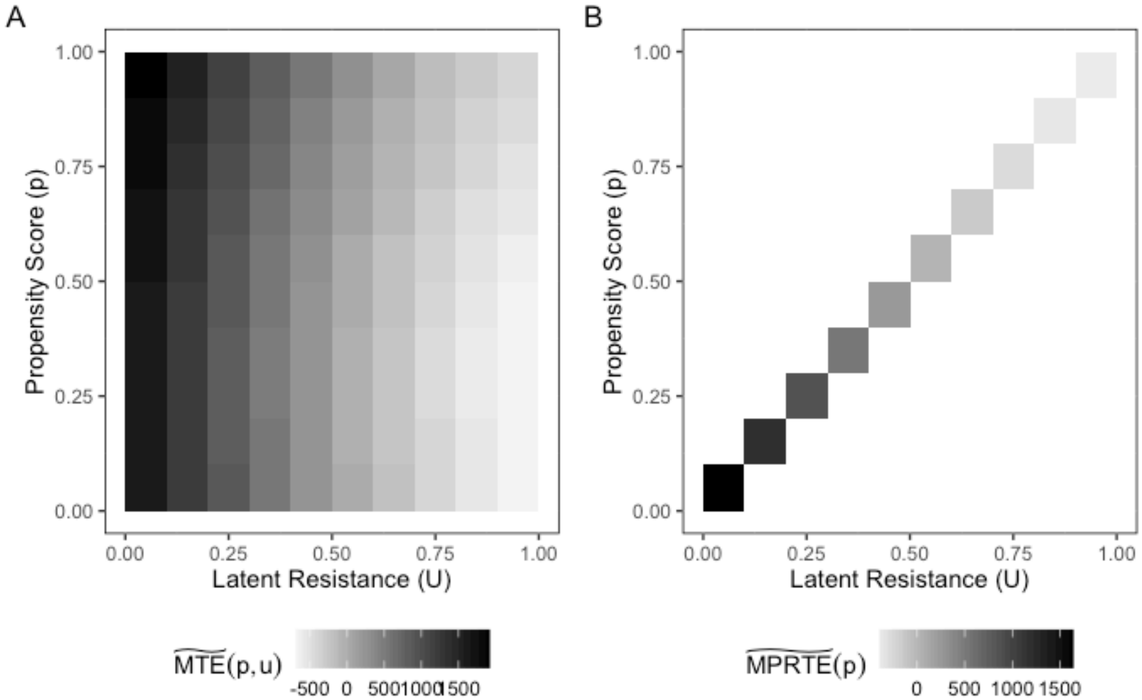

Figure 3.3: Treatment effect heterogeneity based on $\widetilde{MTE}(p,u)$ and $\widetilde{MPRTE}(p)$ for net returns of maize and legume yield (GHS/ha). Note that the darker the colour the higher the treatment effect.

Figures 3.2 and 3.3 (left panels) show that the treatment effect 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 on the basis of their idiosyncratic gains. Conversely, the figures indicate that at each level of U, p increases with increases in the treatment effect, indicating that high resource endowed 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, 2020; Abdul Mumin and Abdulai, 2021).

In contrast, Figures 3.2 and 3.3 (right panels) illustrate 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 treatment effect decreases with increases in p, suggesting that farm households who by observed socio-economic characteristics appear least likely to adopt would benefit more from adoption. This paradox of negative selection among the marginal entrants is due to the unobserved sorting on gain as explained earlier.[4] Similar findings have never been reported in agricultural technology adoption studies to the best of our knowledge.

3.4.3. Impacts of adopting SI practices

Table 3.3 reports the average treatment effect (ATE), treatment effect on the treated (TT), and treatment effect on the untreated (TUT) of adopting SI practices on maize yield and net returns of maize and legume yield, respectively. Overall, Table 3.3 suggests that TT>ATE>TUT, indicating that treated farmers who adopted the SI practices benefited more than non-adopters (TUT). This trend is further confirmed by the heterogeneous patterns in Figure 3.4, which explores the relationship between the causal estimands with p.

Table 3.3: Estimated mean impacts of adopting SI practices

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

Note: Non-parametric bootstrap standard errors in parentheses (500 replications). ***, **, * significance at 1,5 and 10 percent levels, respectively. 1 USD= GHS 5.4. We estimate the parameters using the robust semiparametric approach and estimates were based on $\widehat{MTE}(p,u)$. Table 3.9 A5 reports estimated net returns of maize yield only.

[4] We have also provided a graphical explanation in appendix 3A.

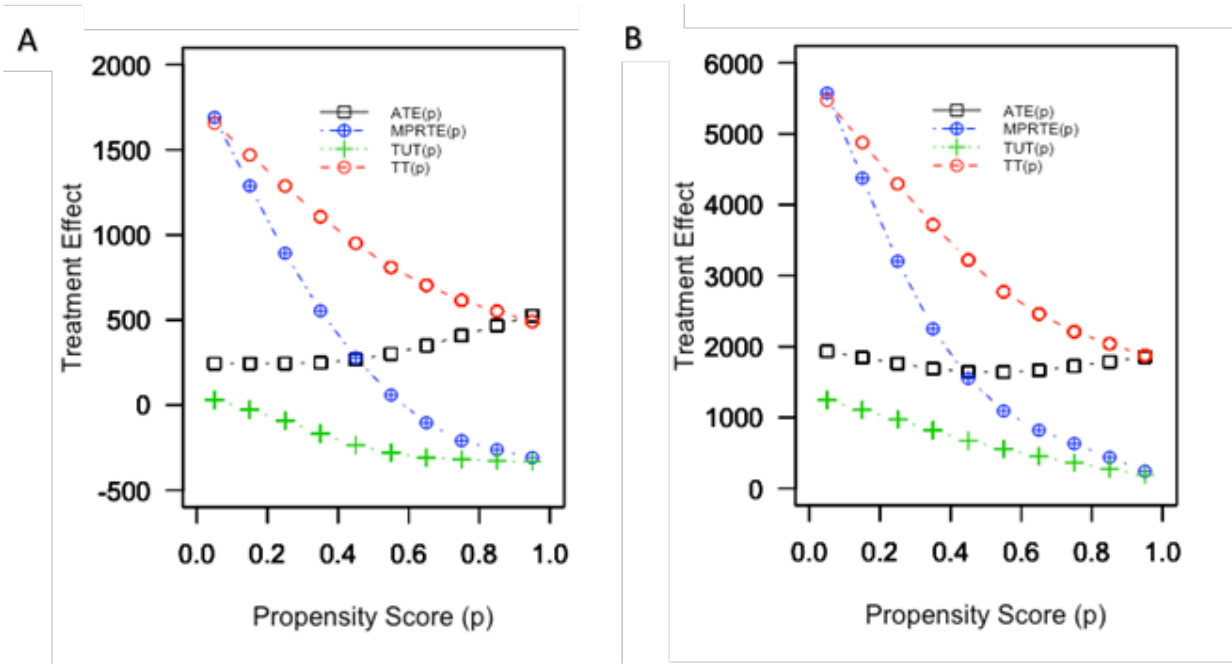

Figure 3.4: Relationship between ATE, TT, TUT and $\widehat{MPRTE}$ at each level of the propensity score for (A) maize yield (kg/ha) and (B) net returns of maize and legume yield (GHS/ha)

Table 3.4 shows that the average maize yield and net returns of maize and legume yield for a randomly selected farmer is around 285 kg/ha and 1907 GHS/ha, respectively. These figures lie between the benefits for the average farmer who adopts (maize yield: 961 kg/ha; maize and legume yield: 3138 GHS/ha), and the benefits for the average farmer who never adopted (maize yield only: -256 kg/ha; maize and legume yield: 911 GHS/ha). We find similar pattern for the net returns when only maize yield is considered in the analysis (Table 3.9A5).

3.4.4. Scaling up policy effects among farmers at the margin of adoption.

It is important to note that the ATE, TT, and TUT estimate the average treatment effects under the policy counterfactual condition that demand mandating adoption and non-adoption of the SI practices. Moreover, they rarely contribute to scaling up policy issues (Heckman and Vytlacil 2005; Mogstad and Torgovitsky 2018).

To address the effects of scaling up the SI practices, we test two distinct policy models: the linear IV and the $\widetilde{MPRTE}$. Here, we test the policy effects of scaling up or expanding the SI practices using the current programme's approach on households at the margin of adoption. For contrast, we follow Carneiro et al. (2011) by using the estimated propensity score or the local instrument from the first stage of the $\widetilde{MTE}(p, u)$ as an instrument in estimating the linear IV model. We note that the estimator in this case estimates the ATE for compliers (Carneiro et al., 2003, 2010,2011; Heckman and Vytlacil , 1999).

However, for the $\widetilde{MPRTE}$, we consider the effect of our policy (α) on four distinct farm household types. That is, we aim at bolstering treatment effect of farm households with different propensity to adopt based on their observed socio-economic characteristics p. Results from such analysis can provide information about how the current programme should be expanded or revised and which farm household should be targeted to maximise returns on scaling up investments.

Our first policy or A-(α) explores the probability of increasing every farm household chance of adopting SI practices by the same unit; the second policy or B-(αp) favours farm households who by observed socio-economic characteristics appear more likely to adopt; the third policy or C-($\alpha(1-p)$) focuses on farm households who by observed socio-economic characteristics appear less likely to adopt; and the fourth policy or D-($\alpha \mathrm{I}(p < 0.20)$) centres on farm households who by observed socio-economic characteristics have about 20% chance of adopting (Zhou and Xie, 2019, 2018).

Table 3.4 presents the scaling up effects of the SI practices at the margin of adoption. The linear IV estimates indicate that the average benefits of adopting the SI practices due to a police change induced by 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 the compliers. However, the $\widetilde{MPRTE}$ explores policy changes that goes beyond the linear IV.

Table 3.4: Estimated benefits of scaling up the SI practices

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

Note. Nonparametric bootstrapped standard errors in parentheses (500 replications). ***, **, * significance at 1,5 and 10 percent levels, respectively. The $\widetilde{MPRTE}(p)$ was estimated using the robust semiparametric approach. 1 USD= GHS 5.4. We used the estimated propensity score or local instrument from the first stage of $MT\widetilde{E(p},u)$ as instrumental variable for the linear IV estimation.

More specifically, Table 3.4 suggests that the third (C) and last (D) scaling up policies would lead to the highest benefits, whereas the second policy (B) would lead to the lowest benefits. We also find similar pattern for the net returns of maize yield only (Table 5A). Table 3.4 also suggests that the average marginal benefits for farmers at the margin of adoption (the first policy (A)) are less than the average benefits of treated farmers who adopted the SI practices (TT). This result implies the need for policymakers to be cautious when using average estimates for scaling up policy decision.

3.4.5. Which farm household will benefit most from scaling up?

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 $MPRTE(p)$, we examine the relationship between the treatment effect, the propensity score p, and the latent resistance U under the four policy changes for maize yield and net returns of maize and legume yield, respectively.

Figures 3.5 and 3. 6 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 benefits. The figures further indicate that not every farm household would benefit from all the potential scaling up policy options. This finding reinforces the need to target the SI practices during scaling up.

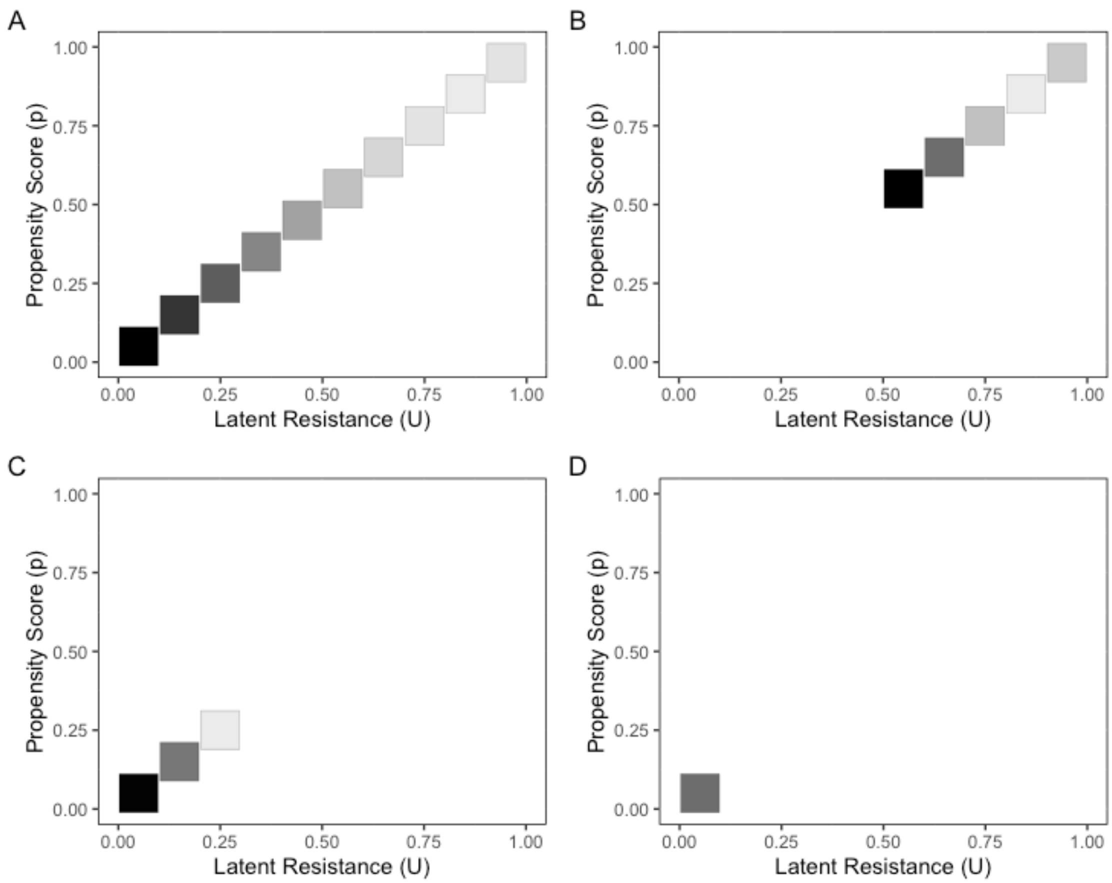

Figure 3. 5: Scaling up SI practices under four policy changes for maize yield (kg/ha) based on $\widetilde{MPRTE}(p)$. Policy A favours all farmers (top left), Policy B favours more resource endowed farmers (top right), Policy C favours less resource endowed farmers (bottom left) and Policy D favours farmers who have 20% chance of adopting the SI practices (bottom right). The darker the colour the higher the treatment effects.

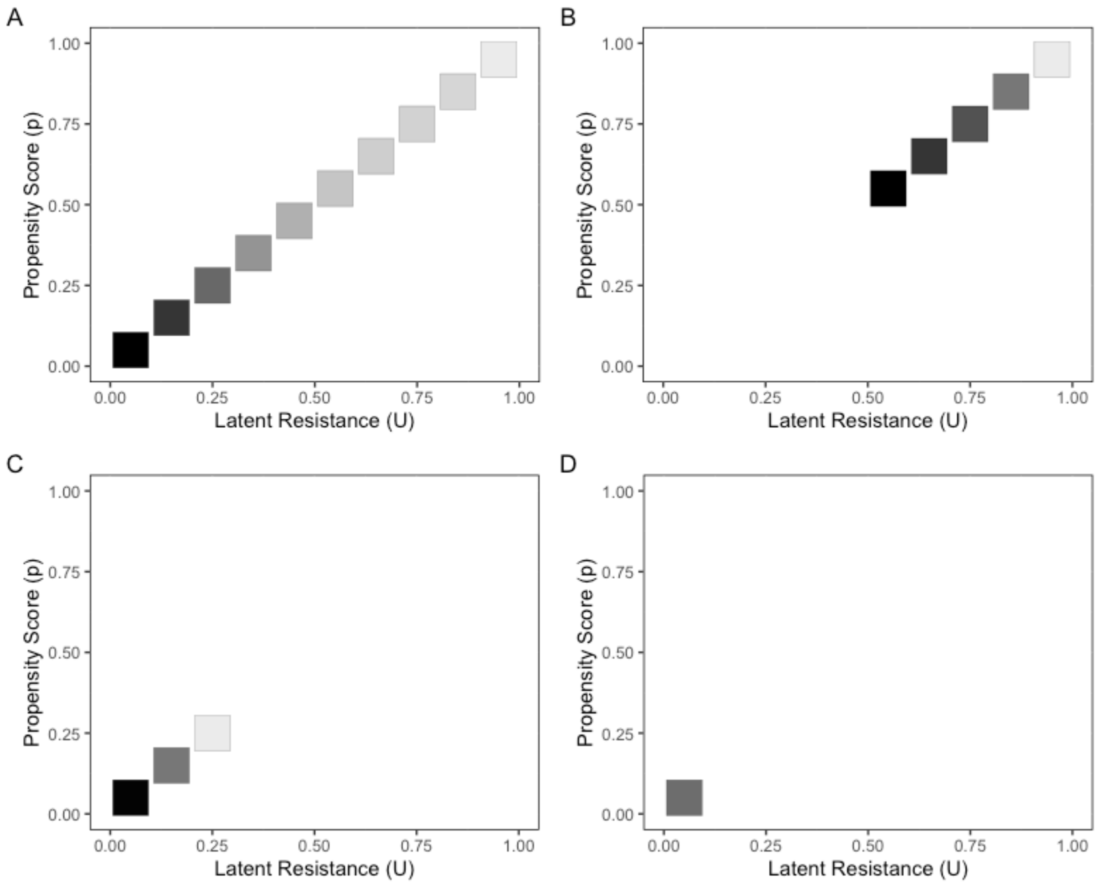

Figure 3 6: Scaling up SI practices under four policy changes for net returns of maize and legume yield (GHS/ha) based on $\widehat{MPRTE}(p)$. Policy A favours all farmers (top left), Policy B favours more resource endowed farmers (top right), Policy C favours less resource endowed farmers (bottom left) and Policy D favours farmers who have 20% chance of adopting the SI practices (bottom right). The darker the colour the higher the treatment effects.

3.4.6. Robustness analysis

We test the sensitivity of our baseline estimates to different model specifications. It is worth noting that in our baseline model, the choice and the outcome equations composed of all the covariates, except the instruments and the baseline maize yield and net returns of maize and legume yield. We included the local instruments in the choice equation only, as well as added to each outcome equation its baseline maize yield or net returns of maize and legume yield in 2013 and the squared.

Table 3.7A3 presents the estimated impacts of adopting SI practices and scaling up options from four different model specifications by modifying our baseline model. In models 1, we include the baseline maize yield and net returns of maize and legume yield in both the choice and outcome equations. In models 2, we include the baseline maize yield, the net returns of maize and legume yield and their squares in the outcome equations only. In models 3, we estimate our baseline model, but also add to the baseline instruments the time taken to reach the nearest market (proxy for distance to market). Here, we envisage that farmers' interactions with market forces would influence their decision to adopt the SI practices, and thus impact positively on their maize yields and net returns. In models 4, we estimate models 3 without accounting for the baseline maize yield and net returns of maize and legume yield in both the choice and outcome equations.

It is worthwhile to note that each of the individual choice model in Table 3.7A3 generates different local instrument, which affects the outcome equation differently. The table suggests that the estimates, including the patterns, are qualitatively similar to the baseline estimates in Tables 3.3 and 3.4. Table 3.8 A4 presents a sensitivity test of our baseline estimates to different bandwidths. The table suggests that the estimates, including the observed patterns, are qualitatively akin to our baseline estimates in Table 3.3 and 3.4.

Furthermore, we adopt the instrumental variable quantile regression (IVQR) approach to confirm the results that low resource endowed farm households will benefit most during scaling up. The IVQR is based on the rank invariance assumption about the unobserved heterogeneity (Heckman, 1997). We employ the IVQR in extrapolating the treatment effect from the LATE to the ATE of a different population (Chernozhukov & Hansen, 2005; Mogstad & Torgovitsky, 2018; Wüthrich, 2020). In another words, we extrapolate the effect from farm households induced by the instruments to adopt to farm households whose choices are not based on the instruments in a different population (Mogstad and Torgovitsky, 2018). In our estimation of the IVQR, we adopt the quantile method via the method of moments approach proposed by Machado and Silva (2019) in estimating the quantile conditional means. We also used the estimated local instrument from each of the model in Table 4 as an instrumental variable in the estimation.

Figure 3.11 A4 plot the IVQR estimates of impacts of adopting SI practices on maize yield and net returns of maize and legume yield of farmers. The figure implies that the QTEs are heterogeneous and decreases across the entire quantile distribution, suggesting that farm households ranked low in the quantile index would benefit more when the SI practices are expanded in a different population. These findings, together with the graphical patterns, mirror the general findings of Figures 3.5 and 3.6.

3.5. Conclusions and policy implications

This paper examined the marginal and the average benefits of adopting sustainable agricultural intensification practices on farmer maize yield, net returns of maize and legume production, and also predicted the marginal farm household entrants that will benefit the most during scale-up, using the newly defined marginal treatment effect framework approach.

Our findings suggested 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 showed that both farmers' unobserved characteristics and resource endowment affected the marginal and average benefits of SI practices adoption differently. Point estimates imply that adoption of SI practices increased farmers' maize yield and net returns. Our analysis indicated that all potential policy options in scaling up SI practices tend to disproportionately favour households least like to adopt based on observed characteristics.

On the policy side, findings of this analysis suggest that policies and programmes directed toward improving crop productivity and farm income among poor rural farm households can be achieved through diffusion of SI practices. Despite the heterogeneity of farming systems in northern Ghana, implying in turn heterogeneity in policy effects during scaling up, our findings indicate the need for policy-makers 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 scaling up of new agricultural technologies could explain the difference in actual performance compared to 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 insofar dis-adoption of improved agricultural technologies are pervasive in SSA. Provision of support services such as strengthening agricultural extension programmes, facilitating farmers' interaction and knowledge exchange through cooperative groups, and boosting mechanization of agricultural time-intensive operations (e.g. land preparation, planting) can help enhance sustained adoption. These policies would require the commitment of key government ministries in collaborating with the private business mechanization sector during the scaling up process.

Appendix 3

Table 3. 5 A1: Differences in mean characteristics of adopters and non-adopters of SI practices

Variable	Adopters		Non-adopters		P-value
	Mean	SD	Mean	SD	
Female	0.270	0.470	0.190	0.400	0.076**
Age of HH	47.26	13.50	47.730	14.52	-0.474
Dependency ratio	1.05	0.650	1.146	0.760	-0.097
Household size	8.642	4.190	8.970	5.480	-0.328
Read and write	0.157	0.360	0.151	0.360	0.010
Group	0.231	0.440	0.108	0.320	0.122***
Extension agent or NGO	0.742	0.425	0.495	0.501	0.248**
Farm size	1.018	0.710	1.781	2.06	-0.763***
Friends	0.190	0.402	0.102	0.309	0.087**
Other farmers	0.084	0.267	0.095	0.292	-0.011
Herd size	2.985	6.070	3.726	7.62	-0.741
Off-farm income	111.70	155.362	154.550	376.530	-42.854
Productive assets	8.154	5.60	8.372	6.800	-0.218
Market	29.89	23.18	33.260	27.030	-3.374
Motorable road	6.136	8.20	6.216	12.720	-0.081
Guinea savannah	0.783	0.436	0.897	0.303	-0.114**
Sudan savannah	0.215	0.436	0.103	0.303	0.111**
Maize yield 2013	949.800	700.730	970.100	677.209	-20.281
Net returns 2013	450.800	2072.499	298.400	2095.309	152.366
Outcome variable					
Maize yield 2018	1115.00	706.326	1052.400	664.713	62.897
Net returns 2018	1298.600	2858.10	444.400	2761.70	853.714**
Observations	299		370		

Note: SD denotes standard deviation. ***, **, * significance at 1,5 and 10 percent levels, respectively. 1 USD= GHS 5.4. The Mann-Whitney test and the Chi-square test were used for the continuous and binary variables, respectively.

Table 3. 6 A2: Test of validity of selected instruments

Variable	Model 1 Decision to adopt (1/0)	Model 2 Net returns of maize and legume yield (GHS/ha)	Model 3 Maize yield (kg/ha)	Model 4 Net returns of maize yield only (GHS/ha)
Sources of information				
Extension agent or NGO	0.610(0.118)***	73.466(312.126)	116.917(74.108)	31.05(91.760)
Group membership	0.272(0.0.156)*	-154.240(524.868)	81.494(126.018)	183.000(155.400)
Friend	0.220(0.166)	260.022(571.333)	11.379(136.903)	202.400(164.300)
Other farmers	-0.366(0.137)**	336.663(552.316)	-4.922(132.183)	202.400(170.700)
Constant	0.221(0.380)	-270.991(932.766)	542.226(233.187)**	1010.200(3032.100)***
Wald test for sources of information	χ2 χ^2=111.8***	F-stat.= 0.299,p=0.879	F-stat.= 0.151, p=0.392	F-stat.=0.889, p=0.471
Sample size	669	370		

Note: Model 1: Probit model (Pseudo R^2 =0.034) Model 2, 3, and 4 : ordinary least squares (Model 2: R^2=0.047; Model 3: R^2=0.068, Model 4: R^2= 0.071). Standard errors in parentheses (clustered at the household level), ***, **, * significance at 1,5 and 10 percent levels, respectively. 1 USD= GHS 5.4. For brevity, we did not report all the parameters.

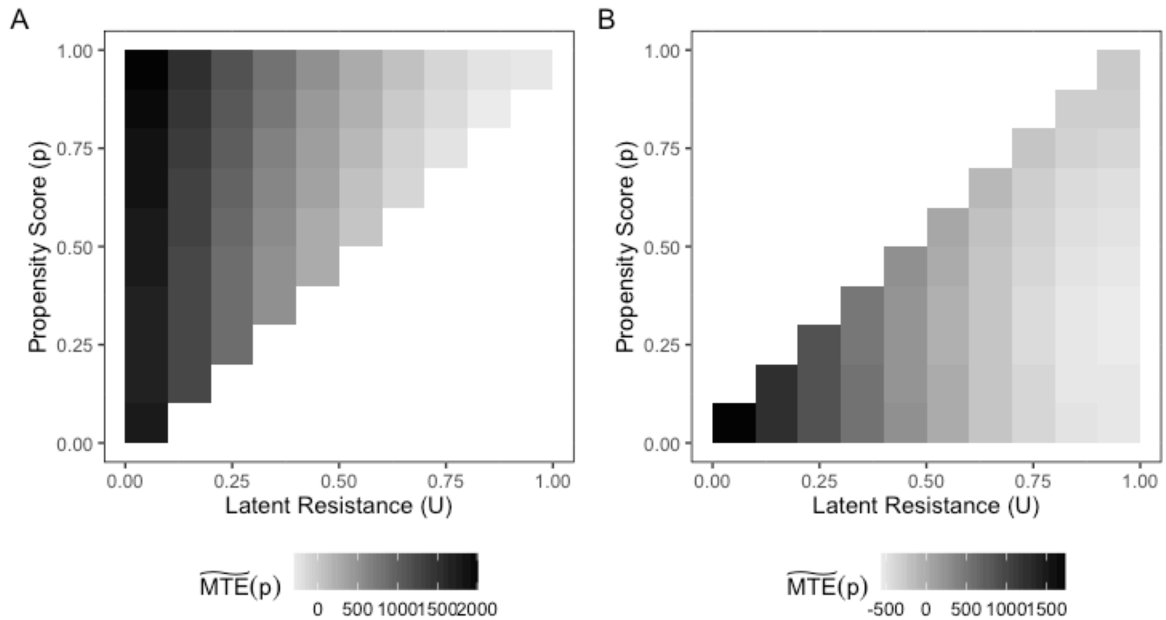

Figure 3.7 A1: Heterogeneity in the treatment effects on the treated (TT)-A, and untreated (TUT)-B for maize yields (kg/ha). The darker the colour the higher the treatment effects. Estimates were based on $\widetilde{MTE}(p,u)$ and $MP\widetilde{RTE}(p)$.

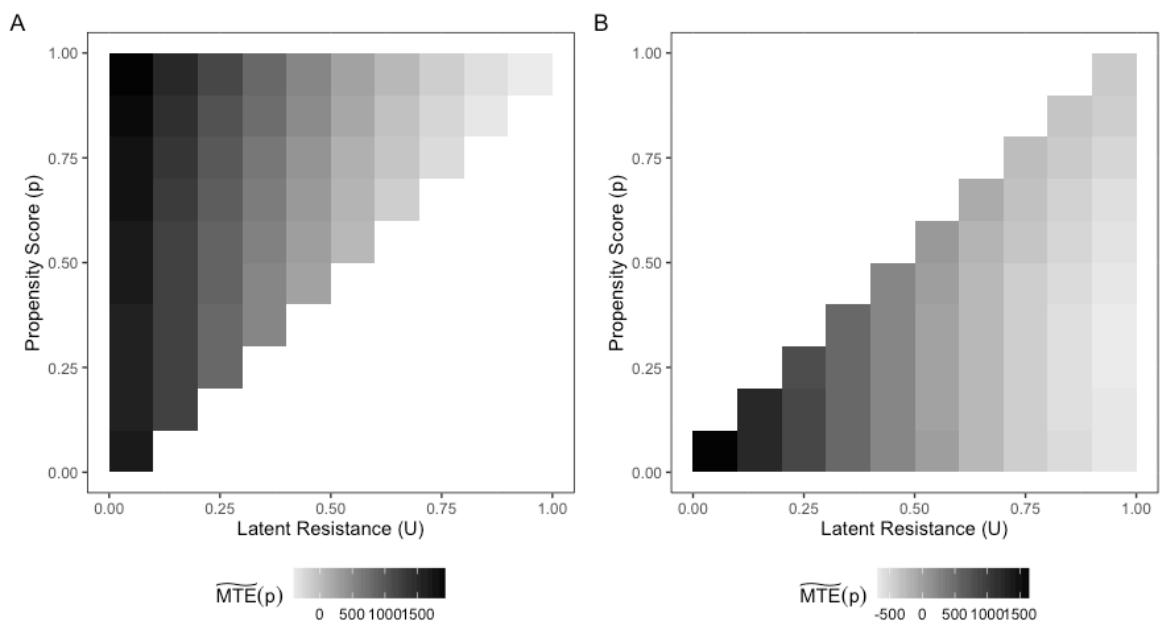

Figure 3.8 A2: Heterogeneity in the treatment effects on the treated (TT)-A, and untreated (TUT)-B for net returns of maize and legume yield (GHS/ha). Darker colour denotes higher treatment effect. Estimates were based on $\widetilde{MTE}(p,u)$ and $MP\widetilde{RTE}(p)$..

Appendix 3A

The equation below denotes the redefined marginal policy relevant treatment effect $\widetilde{MPRTE}(p)$ for farmers at the margin of adoption, where p= u, This is similar to equation (13), and thus all the explanation of the variables still holds here.

$$\widetilde{MPRTE}(p) = \mathbb{E}[\mu_1(X) - \mu_O(X)|P(Z) = p] + \mathbb{E}[\rho|U = p]. \tag{A.1}$$

We note that the equation above consists of two components. The first component reflects treatment effect heterogeneity by the propensity score p, and the second component captures treatment effect heterogeneity by the latent resistance to adopt U. The second component confirmed the established fact that farmers who are more likely to benefit from adoption are most likely to adopt. In other words, the negative relationship between U and ρ, suggests positive selection into treatment or unobserved sorting on gain.

Nonetheless, the first component which aimed at finding out whether farmers who by observed socio-economic characteristics appear more or less likely to adopt benefit from adoption is never studied to the best of knowledge. We note that at the margin of adoption, a stronger negative relationship or a downward sloping of U or $\rho|U$ cancels out the positive association between $p(Z)$ and p, forcing $\widetilde{MPRTE}(p)$ to decline with p (Figure 3.9 A3). Thus, it is the rather the unobserved sorting on gain at the margin of adoption that leads to the negative selection (Zhou and Xie ,2019, 2018).

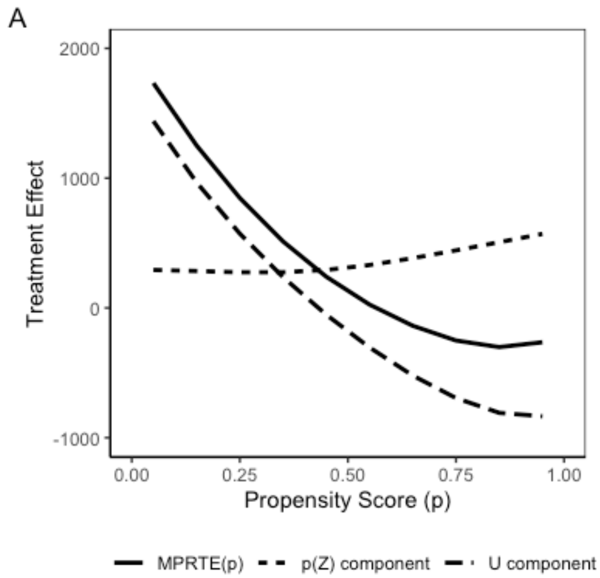

Figure 3.9 A3: Decomposition of $\widetilde{MPRTE}(p)$ for (A) maize yield (kg/ha) and (B) net returns of maize and legume yield (GHS/ha).

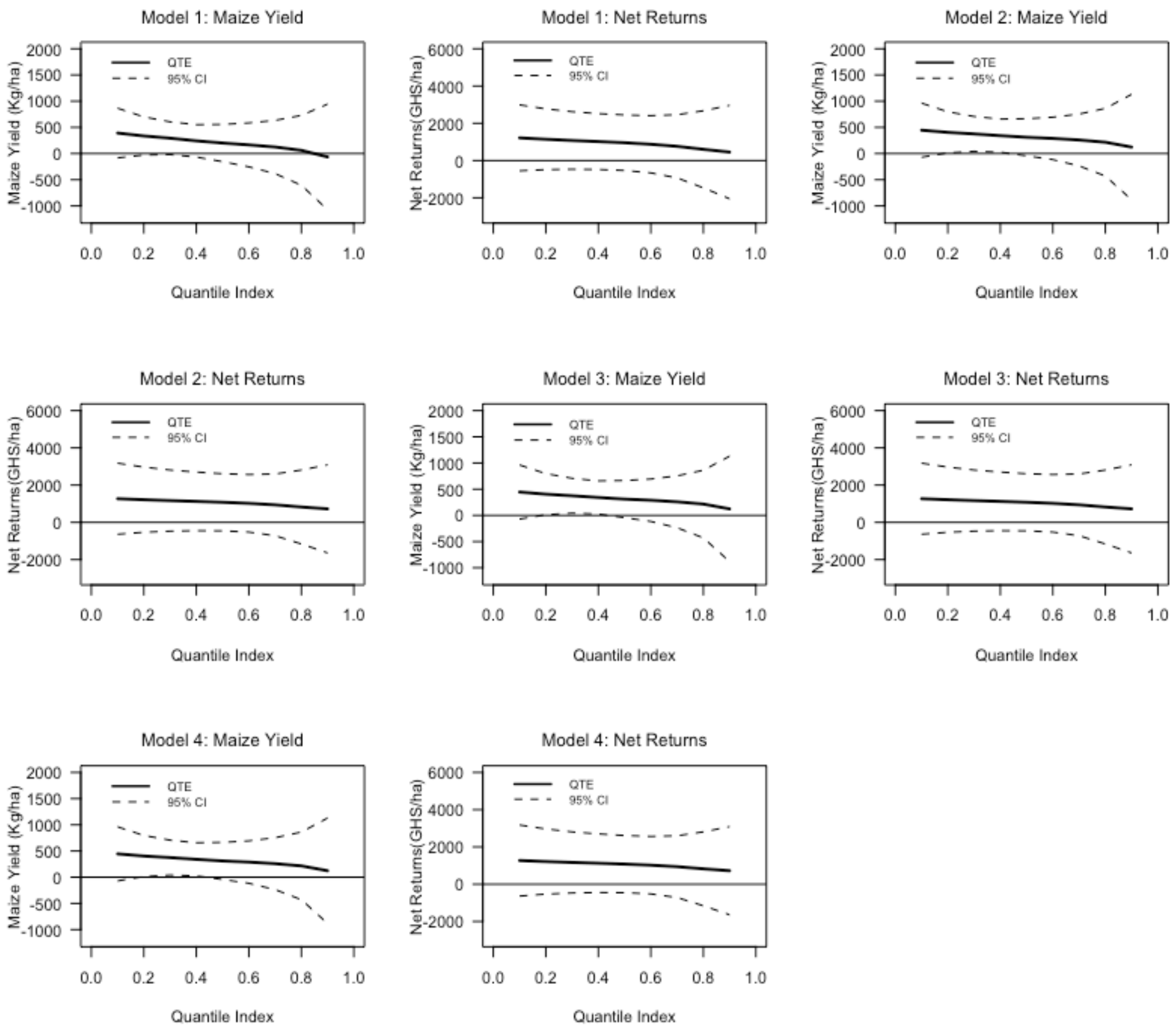

Figure 3.10A4: Extrapolating LATE to ATE with IVQR. Distributional impacts of adopting SI practices on maize yield and net returns of farmers. Solid and dashed lines denote quantile treatment effect (QTE) and 95% confidence intervals, respectively. Models 1, 2, 3, and 4 use the estimated local instruments from the first stage of the models in Table 3.7A3.

Table 3. 7A3: Sensitivity test of impacts of adopting SI practices and scaling up options to different model specifications

Parameter	Maize yield (kg/ha)				Net returns (GHS/ha)			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
ATE	282.987	253.866	329.993	325.541	1907.099*	1893.383*	1976.454*	1961.406*
	(301.362)	(334.772)	(329.809)	(316.982)	(1153.073)	(1272.501)	(1176.891)	(1165.498)
TT	792.459*	907.797**	935.619**	954.850**	3161.069*	2754.851	3131.918*	2942.419*
	(460.848)	(443.810)	(435.648)	(434.120)	(1827.736)	(1908.047)	(1838.542)	(1775.150)
TUT	-127.301	-272.206	-157.280	-180.745	892.4937	1193.417	1041.538	1166.715
	(460.848)	(546.417)	(567.119)	(580.145)	(1905.725)	(1985.233)	(1915.251)	(1958.980)
$\widetilde{MPRTE}$								
$\lambda(p) = \alpha$	347.605	327.263	378.134	384.818	1980.050*	1846.844*	1965.479**	1910.115**
	(245.653)	(265.438)	(261.115)	(250.429)	(973.770)	(1021.183)	(955.063)	(948.345)
$\lambda(p) = \alpha p$	126.296	66.721	128.209	131.202	1346.865	1326.197	1380.689	1407.743
	(278.861)	(296.274)	(306.200)	(305.624)	(1027.629)	(1073.402)	(1019.631)	(1037.273)
$\lambda(p) = \alpha(1-p)$	526.192*	537.973**	580.257**	589.927**	2492.300**	2267.911*	2438.421**	2316.401**
	(280.967)	(290.202)	(274.472)	(268.072)	(1144.729)	(1191.825)	(1139.791)	(1090.737)
$\lambda(p) = \alpha \mathrm{I}(p < 0.20)$	1195.239**	1383.054**	1413.325***	1418.483**	4839.935**	4316.225*	4585.489*	4260.924**
	(574.187)	(561.828)	(532.905)	(534.867)	(2379.236)	(2432.661)	(2373.829)	(2213.400)
Observations				669				

Note: Nonparametric bootstrap standard errors in parentheses (500 replications). ***, **, * significance at 1, 5 and 10 percent levels, respectively. Estimates are all of the robust semiparametric method. 1 USD= GHS 5.4. Models 1 included the baseline maize yield and net returns of maize and legume yield in both the choice and outcome equations. In models 2, we included the baseline maize yield, the net returns of maize and legume yield and their squares in the outcome equations only. In models 3, we estimated our baseline model, but also added to the baseline instruments the time taken to reach the nearest market. In models 4, we estimated our model 3 without accounting for the baseline maize yield and net returns of maize and legume yield in the choice and outcome equations. We used the baseline bandwidth of 0.30. Estimates were all based on $\widetilde{MTE}(p,u)$ and $\widetilde{MPRTE}(p)$.

Table 3. 8 A4: Sensitivity test of baseline estimates to different bandwidths

Parameter	Bandwidth = 0.20		Bandwidth = 0.40		Bandwidth=0.60	
	Maize yield (kg/ha)	Net returns of maize and legume yield (GHS/ha)	Maize yield (kg/ha)	Net returns of maize and legume yield (GHS/ha)	Maize yield (kg/ha)	Net returns of maize and legume yield (GHS/ha)
ATE	420.875	1849.741	253.252	1681.4171*	224.9315	1464.083*
	(395.593)	(1574.118)	(265.281)	(1083.727)	(245.652)	(910.770)
TT	924.089**	3755.282**	759.966*	2861.346*	737.123*	2674.169*
	(472.435)	(1987.800)	(435.141)	(1627.368)	(412.020)	(1667.968)
TUT	16.668	298.268	-154.710	730.521	-187.263	491.1083
	(609.1107)	(2207.744)	(517.553)	(1969.119)	(478.552)	(1814.287)
$\widetilde{MPRTE}$						
$\lambda(p) = \alpha$	375.384	2179.832*	338.272	1779.747*	326.820	1667.935*
	(286.372)	(1156.489)	(226.312)	(914.444)	(224.754)	(855.7792)
$\lambda(p) = \alpha p$	129.626	1424.036	120.918	1179.188	109.539	1063.514
	(318.687)	(1164.856)	(265.128)	(1035.208)	(259.982)	(855.779)
$\lambda(p) = \alpha(1-p)$	573.700*	2791.274**	513.668*	2265.602**	502.156*	2156.914*
	(306.810)	(1338.931)	(258.021)	(1054.867)	(265.363)	(1046.770)
$\lambda(p) = \alpha \mathrm{I}(p < 0.20)$	1428.439**	5858.769**	1138.540**	4126.566**	1098.641**	3804.318*
	(629.427)	(2926.742)	(523.521)	(2060.104)	(509.378)	(2054.946)
Observations			669			

Note: Nonparametric bootstrap standard errors in parentheses (500 replications). ***, **, * significance at 1, 5 and 10 percent levels, respectively. Estimates are all of the robust semiparametric method. 1 USD= GHS 5.4. Baseline bandwidth is 0.30. Note that similar patterns are observed for other bandwidths. Estimates were based on $\widetilde{MTE}(p,u)$ and $\widetilde{MPRTE}(p)$.

Table 3. 9 A5: Estimated mean impact and scaling up effect for net returns of maize yield only

Parameter	Net returns of maize yield only (GHS/ha)
ATE	389.9554
	(414.293)
TT	942.833*
	(526.678)
TUT	-55.023
	(758.104)
$\widetilde{MPRTE}$	
$\lambda(p) = \alpha$	413.620
	(314.722)
$\lambda(p) = \alpha p$	156.874
	(391.664)
$\lambda(p) = \alpha(1-p)$	621.261**
	(324.402)
$\lambda(p) = \alpha \mathrm{I}(p < 0.20)$	1469.357**
	(649.973)
Observation	669

Note: Non-parametric bootstrap standard errors in parentheses (500 replications). ***, **, * significance at 1,5 and 10 percent levels, respectively. 1 USD= GHS 5.4. We estimate the parameters using the robust semiparametric approach. Estimates were based on $\widetilde{MTE}(p,u)$ and $\widetilde{MPRTE}(p)$.

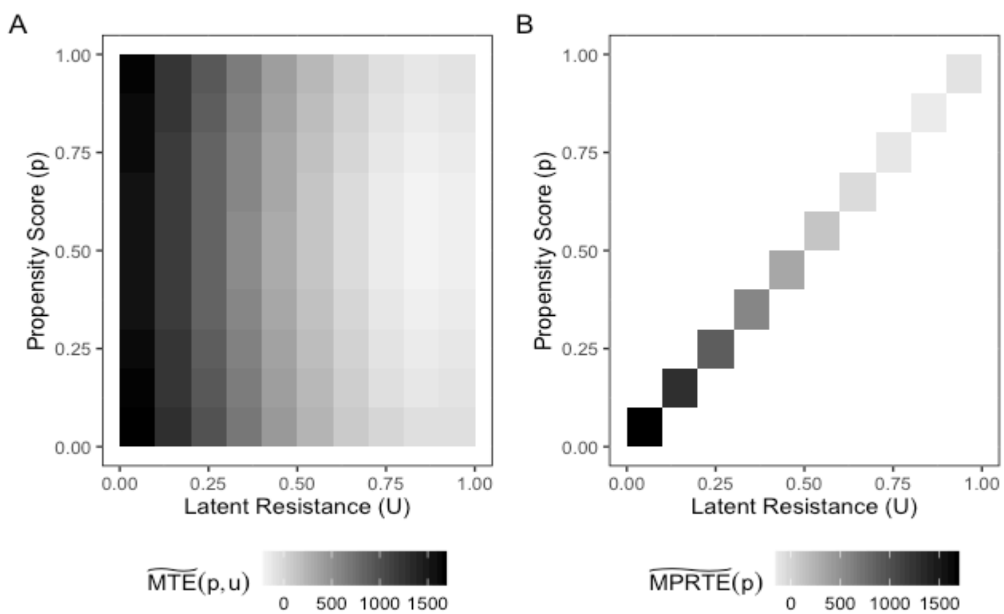

Figure 3.11A5: Treatment effect heterogeneity based on $\widetilde{MTE}(p,u)$ and $\widetilde{MPRTE}(p)$ for net returns of maize yield only (GHS/ha). Darker colour denotes higher treatment effect.

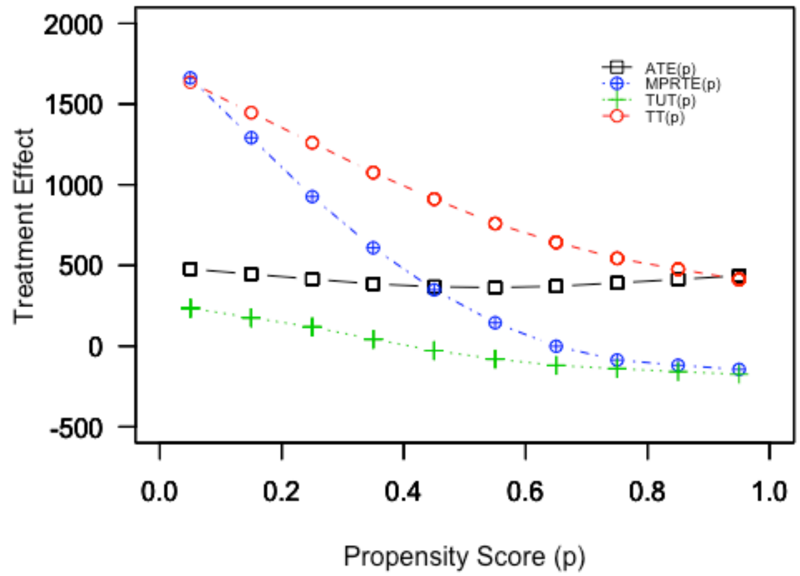

Figure 3.12A6: Relationship between ATE, TT, TUT and $\widetilde{MPRTE}(p)$ at each level of the propensity score for net returns of maize yield only (GHS/ha).

Chapter 4: Disseminating sustainable intensification of agricultural practices: who benefits most?[+]

Abstract

This paper examines both the average and heterogeneous effects of disseminating sustainable intensification of agricultural practices (SI practices) on farmers' net income and farm household welfare in Ghana. The paper also estimates the heterogeneous effects at the subpopulation of adopters as well as identify the characteristics of the farm households that benefited most and least from adoption. Findings indicate that the adoption of SI practices increases net income of maize and legume yield and per capita food expenditure of adopters. Results also reveal that the benefits from adopting SI practices are very heterogeneous across farm households. Estimates indicate that compare to the least beneficiary adopters, the most beneficiary adopters live in highly resource endowed households with relatively younger household heads, fewer household members, and travel longer distances before reaching the nearest market and motorable road.

[+] The essay is co-authored by Nurudeen Abdul Rahman. I conceptualized the research, collected the data, developed the methodology, carried out the formal analysis, and wrote the manuscript. Nurudeen Abdul Rahman commented and edited the manuscript. A version of the essay is under review with Applied Economic Perspectives and Policy.

4.1. Introduction

The adoption literature has documented low adoption of agricultural technologies among farm households, particularly in sub-Saharan Africa (SSA). Reasons ranging from poor road network, lack of access to inputs, inadequate use of fertilisers to differences in agroecological condition have been attributed to the low adoption rates (Ashraf et al., 2009; Duflo et al., 2011; Emerick and Dar, 2021; Giller et al., 2011). However, several new agricultural technologies continue to be developed and disseminated in SSA with the aim of addressing future challenges associated with the expected increases in population (United Nation, 2019; Vollset et al., 2020).

The farming systems in SSA are highly heterogeneous in terms of farmers' resource endowment and agroecological condition (Giller et al., 2009, 2011). Nonetheless, much of the adoption literature focused on the average effect of adopting agricultural technologies and practices (e.g. Kassie et al., 2015; Khonje et al., 2015; Kotu et al., 2017; Manda et al., 2016), although the effect at the average level obscures the heterogeneous effects (Bitler et al., 2006). Few studies have examined the heterogenous effects (e.g. Abdul Mumin and Abdulai, 2021; Adam and Abdulai, 2020). But, the effects at both the average and heterogeneous levels conceal the heterogeneity in the effect at the subpopulation of (non)-adopters and do not reveal the characteristics of the farm households that benefited most and least from adoption.

Furthermore, the heterogeneous nature of the farming systems in SSA (Giller et al., 2009, 2011) suggests that effect from adopting agricultural technologies would vary across farm households and hence there is the need to identify households that benefited most and least from adoption. Failure to account for this in scaling up decision-making would lead to mistargeting of agricultural technologies and practices, which may contribute to poor adoption or dis-adoption in the future. Moreover, already scarce funds are more likely to be wasted when wrong farm households are targeted.

As part of the testing and dissemination of sustainable intensification of agricultural practices (SI practices)[5] in northern Ghana, we examine the average and distributional effects of adopting SI practices on net income of maize and legume yield and per capita food expenditure. We also examine the heterogeneity in the effect at the subpopulation of adopters as well as identify the farm households that benefited most and least from adoption. We situate our study within the context of an agricultural research for development programme in Ghana, where benefits of SI practices have been demonstrated to rural farm households. Similar programme can be found in Mali, Ethiopia, Malawi, Tanzania and Zambia. It is also worth noting that the farming system in Ghana is highly heterogeneous just like most farming systems in SSA (Alvarez et al., 2018; Kamau et al., 2018; Kuivanen et al., 2016).

Our current study contributes to the adoption literature in twofold. First, we estimate the effect of adopting agricultural technology beyond the average effect by also exploring the distributional effects. This is pertinent given the highly heterogeneous nature of the farming systems in SSA. Second, we also contribute to the adoption literature by not only estimating the average and distributional effects but also examine the effects at the subpopulation of adopters. Most studies in economics (e.g. Imai and Ratkovic, 2013; Wager and Athey, 2018) estimate the conditional average treatment effect (CATE) at the subpopulation level, but the CATE fails to fully illustrates the heterogeneous treatment effects at the subpopulation level as well as identify the individuals that benefited most and least from a given intervention (Chernozhukov et al., 2018).

Following Chernozhukov et al.(2018), we adopt the recently proposed sorted treatment effect approach that enables us to examine the heterogeneous effects at the subpopulation of adopters as well as identify the characteristics of farm households that benefited most and least from adoption. To the best of our knowledge this will be the first study in the adoption literature to explore such a route. Understanding who benefited most and least from an intervention can help policymakers in designing effective dissemination strategies to maximise benefits at scale.

[5] We note that the aim of SI practices is to enhance farmers' soil and crop productivity on the same piece of plot or land without necessary expending the plot sizes.

Moreover, it can help in revising existing dissemination strategies if the intended beneficiaries of a programme intervention were to be missed.

Our findings showed that, on average, the adoption of SI practices increases net income of maize and legume yield (over 100%) and per capita food expenditure (ranging between 50 to 70%) of adopters. The distributional analysis indicates that the effects from adopting SI practices are very heterogeneous across the farm households. Our sorted effect estimates reveal that the effects at the subpopulation of adopters are highly heterogeneous and that not all the adopters of the SI practices benefited from adopting. More specifically, a classification analysis of the most and least beneficiary adopters based on the net income of maize and legume yield gap suggests that compared to the least beneficiary adopters, the most beneficiary adopters earned higher net income of maize and legume yield and are more likely live in farm household with higher per capita food expenditure. They are also much more likely to live in farm households that own more livestock and productive assets, have smaller household members and dependency ratio, have relatively younger household heads, and have members expending higher amount of labour in agricultural activities. Finally, they are relatively more likely to travel at longer distances before reaching the nearest weekly market and motorable road.

The rest of the sections is organized as follows. Section 4.2 describes the study context. Section 4.3 presents the conceptual framework and estimation strategies. Section 4.4 presents the results and Section 4.5 provides the conclusions and policy implications.

4.2. Study context

The Africa RISING programme commenced in 2012 across northern Ghana with the aim of lifting farmers out of hunger and poverty via sustainably intensified farming systems. The programme trained households on how to enhance their maize-legume based systems via demonstration and dissemination of sustainable intensification practices.[6] The SI practices were demonstrated to

[6] https://africa-rising.net/

farmers through the use of a technology park, which serves as a learning and dissemination center. The technology park was sited across all the project intervention zones. Farmers were educated on efficient fertiliser application, proper crop spacing, use of improved crop varieties, line sowing, and ways to incorporate legumes into cereal-based systems. The legumes were expected to help reduce farmers' dependency on chemical fertilisers as well as diversify their incomes (Chen et al., 2014; Giller et al., 1997). Farmers were expected to adopt the practices together in order to improve their maize and legume yields.

Prior to the start of the programme, the administrative districts of then three northern regions were stratified into six main domains based on market access and agroecological potentials of the regions.[7] Fifty communities were sampled across the six domains. That is, 25 communities were purposely sampled, and received intervention from the programme, whereas the rest of the 25 communities, randomly sampled, did not received any intervention (Guo and Azzarri, 2013; Tinonin et al., 2016). We termed these communities as non-intervention communities. In 2016, the programme stopped its activity in 13 intervention communities due to lack of funds from the major sponsor.

4.2.1. Study area

Northern Ghana is classified under the Savannah agroecological zone, characterised by one growing season. Farm households in the regions cultivate cereals (e.g. maize, rice), legumes (e.g. cowpea, soybean), root and tuber crops (e.g. yam), and vegetables (e.g. cabbages). Majority of these crops are produced under rain fed agriculture. Some farm households also raise small (e.g. sheep and goat) and large ruminants (e.g. cattle), poultry, and pigs. Nevertheless, the poverty levels among the majority of farm households across the regions are the highest in the country (MoFA 2017).

[7] The regions have been sub-divided into five regions as of now.

4.2.2. Data

The current study is a follow-up of the Ghana Africa-RISING Baseline Survey conducted in 2014 where 1248 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.[8] 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. On the whole, based on the power analysis, we sampled 212 and 217 households from the continued and dropped out communities, respectively, and 271 farm households from the non-intervention communities. We note that the continued and dropped-out communities included farm households not directly trained by the programme (i.e. 40 and 48 for continued and dropped-out respectively). However, for the purpose of this study, we excluded these farm households from the analysis.

Furthermore, using the same baseline questionnaire, a team of trained research assistants conducted face-to-face interviews with the sampled households across the regions. Information solicited from the farmers covered socio-economic characteristics of the household, crop production, storage to food and nutrition security.

Finally, since farmers are expected to adopt all the practices together in order to enhance their soil and crop productivity and net incomes, in this study we consider adopters of SI practices as farmers who have applied the SI practices on their plots for more than one cropping season after 2015. This is to capture not only adopters of the SI practices but also the intensity of application

[8] 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 of attrition and non-responses to questions.

of the practices. In all, 287 farm households continued to adopt the SI practice, whereas the rest, 327 farm households, did not (Table 1A).[9]

4.2.3. Variable 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 (e.g. gender, age, educational background), dependency ratio, household size, farm size, number of livestock, access to extension service, number of productive assets, off-farm income, the time taken reach the nearest market or motorable road, and the average amount of labour expended by farmers on the entire agricultural production per season.

For the outcome variables, we focused on net income of maize and legume yield and per capita food expenditure. We estimated the net income of maize and legume yield as the total value of harvested maize and legume yield multiplied by their respective average village prices in Ghana cedi less the cost of production (including family labour) in Ghana Cedis per hectare (GHS/ha). We estimated the per capita food expenditure as the total amount spent on food consumption either from market purchases, own production or other purchases divided by the household size. We note that our food expenditure proxy household food security and economic access to food. Thus, an increase in the food expenditure of a farm household would indicate that the quantity and/ or quality of food consumed by the household has improved (Debela et al., 2020).

Table 4.1 presents the summary statistics of our sample farm households and the description of variables used. The table implies that majority of the household heads are male, and the average age of a given households is about 48 years. About 85% of the households cannot read and write and around 75% of the households source their agricultural information from extension services. The table also suggests that the average farm size and herd size of a given households are 1.46

[9] Farm households were mainly from the non-intervention (271) communities, followed by dropped out (44) and continued (12) communities.

hectares and about 4 TLU, respectively. The table further indicates that the average net income of maize and legume yield and per capita food expenditure per day are around 932 Ghana cedis per hectare (GHS/ha) and about 8 GHS, respectively.

Furthermore, Table 4.5A1 presents the mean characteristics between the covariates of adopters and non-adopters and their respective P-values. The table implies a significant difference for gender, farm size, group membership, labour expended by male and female farmers, access to extension services, Northern, Upper East, Upper West, and net income of maize and legume yield between adopters and non-adopters.

Table 4.1: Summary statistics and explanation of variables used

Variable	Explanation	Mean	SD
Female	Gender of household head(1=female,0=otherwise)	0.168	0.374
Age	Age of household head in years	47.899	13.738
Household size	Total number of household members	8.938	5.031
Dependency ratio	Number of children under 15 and elders above 65 divided by the number of adults between 15-64	1.082	0.712
Livestock size	Total livestock in tropical livestock units	3.477	6.869
Read and write	Household head can read and write (1=yes, 0=otherwise)	0.147	0.354
Market	Minutes taken to reach the nearest weekly market	32.58	26.050
Assets	Total number of durable assets	8.366	6.470
Farm size	Total crop area in hectares (ha)	1.463	1.717
Off farm income	Household head engages in off-farm income activities (1=yes, 0 otherwise)	0.713	0.453
Northern	Northern region (1 =yes, 0 otherwise)	0.4935	0.500
Upper East	Upper East region (1 =yes, 0 otherwise)	0.168	0.374
Upper West	Upper West regions (1 =yes, 0 otherwise)	0.339	0.474
Extension	Access to extension services (1 =yes, 0 otherwise)	0.748	0.435
Group membership	Household member belong to FBO (1 =yes,0 otherwise)	0.191	0.393
Motorable	Time taken to reach the nearest motor able road in minute	6.248	11.349
Female labour	Average labour expends by female in person-days	28.992	23.003
Male labour	Average labour expends by male in person-days	38.497	35.582
Outcome variable			
Net income of maize and legume yield	Net income of maize and legume yield in Ghana Cedis per hectare (GHS/ha)	932.450	2862.932
Per capita food expenditure	Per capita food expenditure in GHS per day	8.536	10.362
Observations		614	

Note: SD denotes standard deviation. FBO denotes farmer-based organisation.

4.3. Conceptual framework and estimation strategies

4.3.1. Conceptual framework

We expect the adoption of SI practices to enhance farmers' soil productivity leading to increases in crop productivity. In addition, we expect the adoption of legumes to fix atmospheric nitrogen into soil (Giller et al., 1997; Vanlauwe et al., 2019). We envisage that all these will contribute to enhancement of farmers' maize and legume yields, net incomes, and farm households' per capita food expenditure. Following Abdulai and Huffman (2014), we assume farmers are risk neutral and will adopt the SI practices if the associated net benefits are greater than those from alternative practices. That is, given that Y_1 represents the returns from SI practices adoption and Y_0 the returns from non-adoption, farmers will adopt SI practices if $Y_1 > Y_0$ (Pitt 1983).

4.3.2. Estimation strategies

Following Heckman and Vytlacil, (2007) and Belloni et al.(2017), we adopt the potential outcome framework in estimating the average causal effect or average treatment effect (ATE) of adopting SI practices as:

$$Y = dY_1 + (1 - d)\,Y_0 \qquad (1)$$

where Y is the observed outcome, Y_1 is the outcomes of adopters of the SI practices and Y_0 is the outcomes of non-adopters. d is a dummy variable indicating whether a farmer adopted the SI practice ($d = 1$) or not ($d = 0$). We estimate the average causal effect by employing different estimators with varied estimation assumptions. We control for characteristics of (non)-adopters (e.g. educational level of household head, household size) in estimating the average causal effects. Since treatment of farmers in the intervention communities were not randomly assigned, farmers are more likely to self-select into treatment, and thus, we employ the proposed two stage least squares (2SLS), and the Probit-2SLS approaches due to Cerulli (2014), and the instrumental variable least absolute shrinkage and selection operator (IV-Lasso) due to Belloni et al (2014a, 2014b, 2017) in estimating the average causal effect. In contrast with the 2SLS, the Probit-2SLS is estimated under the assumption that treatment effect is heterogeneous across the farm households and thus estimates obtained tend to be more efficient than the 2SLS method (Cerulli, 2014). The IV-Lasso employ here is based on a theory driven and a machine learning method, which selects the appropriate covariates for the estimation (Belloni et al, 2014a, 2014b, 2017).

4.3.3. Distributional effects of adopting SI practices

It is worthwhile to note that the average effect masks the heterogeneous effects of adopting SI practices. Moreover, policymakers are often much more interested in finding out the effect of a given policy on an outcome at the lower tail distribution. Thus, we explore the distributional effects of adopting SI practices on farmers' net income of maize and legume yield and per capita food expenditure. We employ the instrumental quantile regression method (IVQR) due to Chernozhukov and Hansen (2005) in examining the distributional effects. We estimate the IVQR model of the form:

$$Y_d = q(d, x, U_d), \text{ where } U_d \sim U(0,1) \tag{2}$$

and quantile $q(d, x, \tau)$ denotes the conditional τ-quantile of outcome Y_d. We note that U_d is a rank variable, which is responsible for heterogeneity of outcomes among households of the same characteristics and treatment status d. We adopt the instrumental variable quantile regression approach due to Chernozhukov et al. (2015) and Lee (2007) in estimating the quantile estimates. As a robustness check, we also estimate the model using the standard quantile regression due to Koenker and Bassett (1978).

4.3.4. Who benefited most and least from adoption

It is worth noting that the average and distributional effects estimates do not shed light on the heterogeneity of the treatment effects at the subpopulation of adopters and do not uncover the farm households who benefited most and least from adoption. Thus, we adopt the sorted effect approach due to Chernozhukov et al. (2018) in exploring the heterogeneous effects of adopting SI practices at the subpopulation of adopters as well as identify the characteristics of adopters that benefited most and least from adoption.

The sorted effect approach helps to examine both the partial effect or predictive effect (PE) and heterogeneity in the PE compare to the average partial effects (APE) or subgroup analysis often employed in most economic studies (Chernozhukov et al., 2018). We follow Chernozhukov et al.(2018) in estimating the sorted effect. We estimate a linear interactive model using a non-additive error or the quantile regression model of the form:

$$Y = g(h) = P(T, x)^T \beta(\epsilon), \qquad \epsilon | T, x \sim \mathrm{U}(0,1), \qquad h = (T, x, \epsilon) \tag{3}$$

where T is the treatment effect of interest or the key covariate d, ϵ is the unobserved rank, and $P(T,x)^T\beta(\epsilon)$ is the conditional τ-th quantile of Y given T and x. We note that the vector $h = (T, x, \epsilon)$, a collection of transformation of T and x, also includes the unobserved rank or factors (e.g. ability rank). The PE is estimated as the difference between the τ-th quantile of the outcome variable of adopters and non-adopters conditional on a particular value of the characteristics x. That is:

$$\triangle\, h = P(1,x)^T\beta(\tau) - P(0,x)^T\beta(\tau), \quad h = (T, x, \tau). \tag{4}$$

We note that the PE $\triangle\, h$ is the function of x and thus it varies across the farm households. Hence to summarise the PEs across the farm households, we employ the sorted predicted effects (SPE), which presents the entire set of values of the PEs sorted in ascending order and indexed by a ranking $u \in (0,1)$ with respect to the population of interest. We note that the SPE reports the full heterogeneity in the PE. In addition, the position of the PE and the SPE helps classify the observations into most and least beneficiary adopters (Chernozhukov et al., 2018). Finally, we note that the APE is akin to the conditional average treatment effect (CATE) (Chernozhukov et al., 2018).

4.3.5. Dealing with endogeneity issues

Since treatment was not randomly assigned in the intervention communities, farmers are more likely to self-select into treatment and thus both farmers observed and unobserved factors (e.g. innate managerial ability) would bias the estimates if they are not accounted for in the model estimations. We follow Di Falco et al. (2011) by using potential information sources (extension services and group membership) about the SI practices as instrumental variables. We expect that the information sources about the SI practices should only influence farmers' decision to adopt SI practices and not directly on the outcome variables (e.g. per capita food expenditure, net income of maize and legume yield). We conducted a falsification test to confirm the validity of the instruments. We found that the instruments affected the decision to adopt the SI practices jointly (χ^2= 183.88, p=0.000) and not on the net income of maize and legume yield (F-stat.= 1.49, p= 0.227) and the per capita food expenditure (F-stat.= 1.240, p=0.290) as depicted in Table 4.6A2. We also checked if the instruments correlate strongly with the outcome variables. Our finding indicated insignificant correlation between the instruments and the outcome variables (Table 4.8A5).

4.4. Results

4.4.1. Average and distributional effects

Table 4.2 presents the average effect of adopting SI practices on net income of maize and legume yield and per capita food expenditure. Overall, the estimates for the 2SLS, the Probit-2SLS and the IV-Lasso are qualitatively the same, although their estimation and identification approaches are different. Specifically, the 2SLS, the Probit-2SLS and the IV-Lasso estimates suggest that the adoption of SI practices led to a positive and statistically significant effect on farmers' net income of maize and legume yield and per capita food expenditure (except IV-Lasso), suggesting that the adoption of SI practices enhances the net income of maize and legume yields and household welfare of farmers.

Table 4.2: Average effects of adopting SI practices

Estimator	Net income of maize and legume yield (GHS/ha)		Per capita food expenditure (GHS)	
	Estimate	SE	Estimate	SE
2SLS	1522.006*	907.209	5.070**	2.584
Probit-2SLS	1940.831*	1030.239	6.277**	3.243
IV-Lasso	1848.123 **	890.1565	5.122	3.412
Observations		614		

Note. SE denotes robust standard error. *p<0.10, **0.05, p<0.05, ***p<0.01. IV-Lasso denotes the least absolute shrinkage and selection operator. We note that the 2SLS and IV-Lasso account for homogeneous treatment effects, while the Probit-2SLS accounts for heterogeneous treatment effects

However, the average effect masks the heterogeneous effect of adopting SI practices since its averages both the positive and negative effects, and thus we explore the distributional effects. Figures 4.1 and 4.2 illustrate the distributional effects of adopting SI practices on net income of maize and legume yield and per capita food expenditure, respectively. The QE and CI represent the quantile effect and the 90% confidence intervals, respectively. Figures 4.1 and 4.2 on the left report the estimates for the instrumental variable quantile regression (IVQR), while those on the right present the estimates for the standard quantile regression (QR).

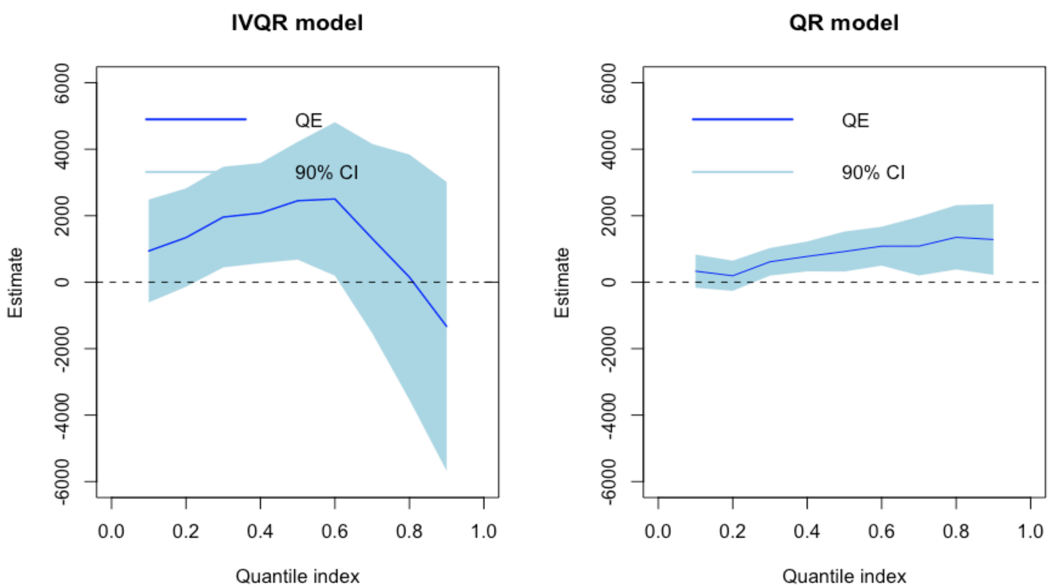

Figure 4.1: Distributional effects of adopting SI practices on net income of maize and legume yield (GH/ha). The 90% bootstrap confidence intervals were obtained with 300 repetitions. We note that the QR model did not account for sample selection bias, compare to the IVQR which control for selection bias.

The QR model of figure 4.1 shows that the effect of adopting SI practices on farmers' net income of maize and legume yield is positive throughout the quantile distribution, but the estimates are downward bias. In contrast, the IVQR estimates show that the effect is highly heterogeneous throughout the quantile distribution, implying that the effect of adopting SI practices on farmers' net income of maize and legume yield are not the same across all the farm households. More specifically, the IVQR estimates are positive throughout the quantile distribution with the exception at quantile 90. We find positive and statistically significant effects between quantiles 20 to 60, indicating that farmers between these quantile indexes experienced positive and significant increases in their net income of maize and legume yields.

For per capita food expenditure, the QR estimates of figure 4.2 are downward bias throughout the quantile distribution. In contrast, the IVQR estimates indicate that the effects are very heterogeneous throughout the quantile distribution, implying that the welfare effects of adopting SI practices vary across the farm households. We further find that the effects below quantile 20 are positive and statistically significant, suggesting that farmers below quantile 20 had higher per capita food expenditure.

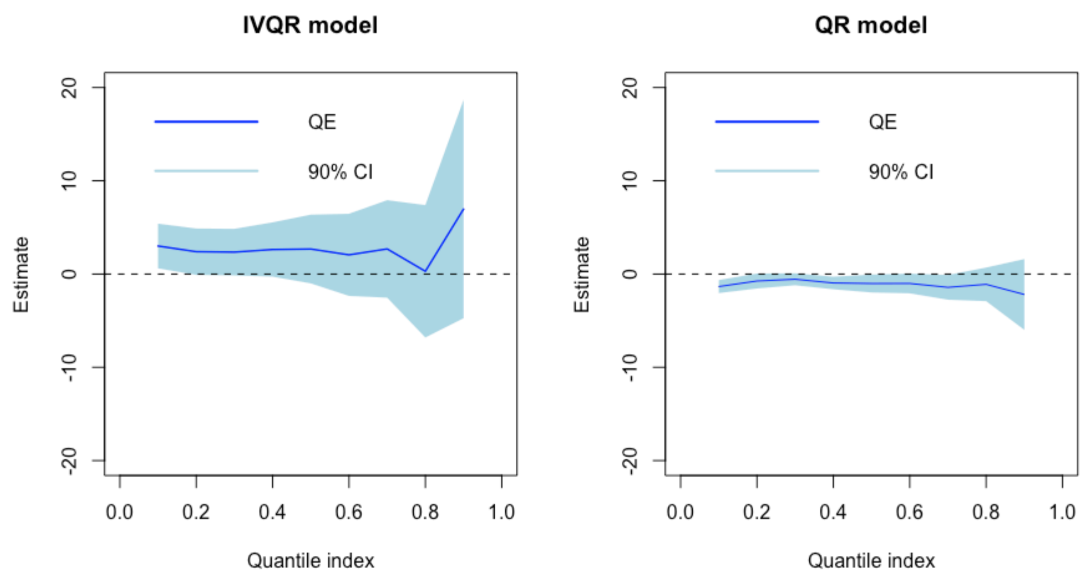

Figure 4.2: Distributional effects of adopting SI practices on per capital food expenditure (GHS). The 90% bootstrap confidence intervals were obtained with 300 repetitions. We note that the QR model did not account for sample selection bias, compare to the IVQR which control for selection bias.

In summary, our average effects suggest that the adoption of SI practices improves household net income and welfare. Our findings support studies (e.g. Kim et al., 2019; Kotu et al., 2017) that have examined the effects of adopting SI practices on crop productivity and net income of farmers. Moreover, the distributional estimates support other studies (e.g. Abdul Mumin and Abdulai, 2021; Adam and Abdulai, 2020) that have evaluated heterogeneous effects of adopting sustainable agricultural practices on crop productivity and household welfare

4.4.2. Who benefited most and least from adoption

It is worth noting that the average and distributional effects estimates do not shed light on the heterogeneity of treatment effects at the subpopulation of adopters and also failed to answer policy relevant questions of who benefited most and least from adoption and what are the characteristics of these farm households. Since we expect farm households with higher net income of maize and legume yield should have higher per capita food expenditure, we estimate our SPE using a linear interactive model based on the net income of maize and legume yield gap. That is, we employ a non-additive error (quantile model) method. For contrast, we also estimate the model using an additive error approach (or OLS model).

Figure 4.3 presents the treatment effect heterogeneity at the subpopulation of adopters by the net income of maize and legume yield gap. The SPE and the APE denote the sorted predictive effect and the average partial effect, respectively. The CB denotes the 90% confidence bands for both the SPE and APE. For contrast, the 90% CB for the quantile and OLS models were estimated using weighted and empirical bootstraps, respectively, with 300 repetitions.

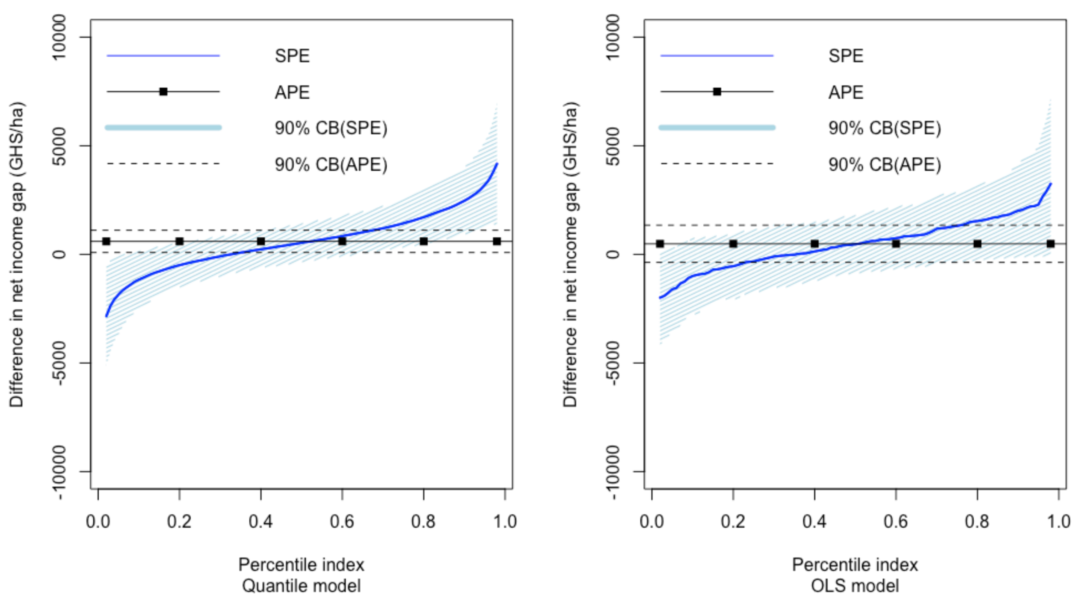

Figure 4.3: The SPE and APE of net income of maize and legume yield gap. Estimates and 90% confidence bands were estimated using a linear interactive model based on quantile (left) and OLS (right) models. The 90% confidence bands were based on the weighted (left) and empirical (right) bootstraps with 300 repetitions.

In general, figure 4.3 shows that the APEs are constant for the two models (about 598 GHS for the quantile model and around 486 GHS/ha for the OLS) and thus disregard the heterogeneity in the treatment effects at the subpopulation of adopters. Conversely, the SPEs suggest that the effects are highly heterogeneous (ranging from around -2850 to 4170 GHS/ha for the quantile model and -1994 to 3248 GHS/ha for the OLS model) at the subpopulation of adopters and that there are winners and losers (negative effects at lower end of the percentile index) of adopters of the SI practices, although the majority benefited. The observed heterogeneity in the effect at the subpopulation of adopters may be attributed to differences in the resource endowment or socioeconomic characteristics of the farm households, and thus we examine these differences.

Table 4.3 presents the results of our classification analysis, showing the characteristics of most and least beneficiary adopters based on the net income of maize and legume yield gap with their respective standard errors (SE) obtained using a weighted bootstrap. We estimate Table 4.3 using the non-additive method (or a quantile model). According to the model, the 20% least beneficiary adopters derive a lower net income of maize and legume yield, have a lower per capita food expenditure, are from male headed farm households, live in households whose heads are older and cannot read and write and live in households typified by higher dependency ratio.

Furthermore, the least beneficiary adopters are much more likely to live in households that own less livestock, have more plot sizes, have less productive assets and the household heads are less likely to engage in off-farm income activities. They are also much more likely to live in the Upper West region, less likely to belong to a group and have less access to extension services, and are much more likely to live in households where female expend less amount of labour in agricultural activities. Finally, they spend less amount of time in reaching the nearest weekly market and motorable road.

Table 4.4 test if the differences reported in Table 4.3 are statistically significant. The p-value accounts for the simultaneous inference on all the variables within the categories and non-categories. For example, the p-value accounts for the fact that we are conducting three tests corresponding to three variables under the regions, whereas, for the non-categories such as age and household size, the p-value is for only one test.

Table 4.3: Mean characteristics of the 20% least and most beneficiary adopters- classification analysis

Variable	Least	SE	Most	SE
Female	0.453	0.016	0.063	0.015
Male	0.547	0.016	0.938	0.015
Age	48.872	0.532	41.813	0.571
Household size	7.756	0.227	5.563	0.226
Dependency ratio	0.930	0.027	0.793	0.030
Read-write, no	0.895	0.014	0.438	0.014
Read-write, yes	0.105	0.014	0.563	0.014
Livestock size, log	0.990	0.033	1.167	0.034
Market, log	1.184	0.018	1.467	0.019
Asset, log	0.812	0.014	0.824	0.014
Farm size, log	0.286	0.007	0.204	0.008
Off-farm income, no	0.267	0.018	0.250	0.017
Off-farm income, yes	0.733	0.018	0.750	0.017
Northern region	0.058	0.022	0.438	0.021
Upper East region	0.081	0.017	0.563	0.016
Upper west region	0.860	0.017	0.000	0.017
Extension service, no	0.384	0.020	0.188	0.021
Extension service, yes	0.616	0.020	0.813	0.021
Group, no	0.919	0.015	0.188	0.016
Group, yes	0.081	0.015	0.813	0.016
Male labour, log	1.226	0.015	1.376	0.014
Female labour, log	1.339	0.013	1.330	0.014
Motorable	0.568	0.018	0.613	0.018
Net income of maize and legume yield	929.828	120.287	2550.182	127.384
Per capita food expenditure	3.784	0.427	30.357	0.419
Observations		614		

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions.

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Table 4.4 suggests that the observed differences in Table 4.3 are significant for some of the variables. That is, Table 4.4 suggests that the 20% least beneficiary adopters earn a lower net income of maize and legume yield and have a lower per capita food expenditure. They are also much more likely to live in a farm household whose head is older, have a higher dependency ratio and have larger household members. Furthermore, they are more likely to live in households that own less amount of livestock and productive assets, but own large plot sizes. They are also much more likely to live in farm households where female farmers expend less amount of labour in their agricultural activities, and are much closer to the nearest weekly market and motorable road.

Table 4.4: Bias corrected difference in mean characteristics of the 20% least and most beneficiary adopters -classification analysis

Variable	Estimate	SE	P-value
Female	0.391	0.005	0.413
Male	-0.391	0.005	0.413
Age	7.060	0.206	0.000
Household size	2.193	0.070	0.000
Dependency ratio	0.137	0.010	0.000
Read-write, no	0.458	0.005	0.427
Read-write, yes	-0.458	0.005	0.427
Livestock size, log	-0.177	0.011	0.000
Market, log	-0.283	0.007	0.000
Asset, log	-0.012	0.005	0.004
Farm size, log	0.082	0.003	0.000
Off-farm income, no	0.017	0.007	0.517
Off-farm income, yes	-0.017	0.007	0.517
Northern region	-0.379	0.006	1.000
Upper East region	-0.481	0.005	1.000
Upper west region	0.860	0.008	0.517
Extension services, no	0.196	0.006	1.000
Extension services, yes	-0.196	0.006	1.000
Group, no	0.731	0.005	0.550
Group, yes	-0.731	0.005	0.550
Female labour, log	-0.151	0.005	0.000
Male labour, log	0.009	0.004	0.012
Motorable	-0.045	0.007	0.000
Net income of maize and legume yield	-1620.354	36.697	0.000
Per capita food expenditure	-26.573	0.137	0.000
Observations		614	

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions. The p-values are adjusted to control for joint testing of zero coefficients on all the variables within the categories. The p-values for non-categories are for a single test.

Overall, tables 4.3 and 4.4 indicate significant heterogeneity in the net income of maize and legume yield gap and relates this heterogeneity to farm household resources (e.g. number of livestock and productive assets, amount of labour expended), demographic characteristics (e.g. age of household head, household size), access to markets and road, and per capita food expenditure. This implies that farmers' resource endowment account for the heterogeneity in the benefits across the subpopulation of adopters.

4.4.3. Mechanism

We explore the potential mechanisms for the effects of adopting SI practices on net income of maize and legume yield and per capita food expenditure. Given the importance of maize as a major staple crop in SSA, including Ghana and its high demand in the northern regions of Ghana, we expect that farmers will adopt SI practices if it increases farmers maize yields and household incomes. Thus, we examine both the average and heterogeneous effects of adopting SI practices on maize yield and household income per month. We employ the same baseline estimators (2SLS, Probit-2SLS, IV-Lasso, and IVQR) in estimating the mean and distributional effects.

Table 4.9A5 presents the effects of adopting SI practices on farmers' maize yields and household incomes per month. The table shows that, on average, the adoption of SI practices had positive and significant effect (except for the 2SLS) on farmers' maize yields and household incomes. We also find that the effects are highly heterogeneous across the farm households and find positive and significant effects at the lower tail of the quantile distribution.

4.4.4. Sensitivity analysis

Using the same linear interactive model employed in examining the average characteristics and differences for the 20% most and least beneficiary adopters, we test the sensitivity of our estimates to different proportion (10%, 40%, and 60%) of the adopters. Tables 4.11A7 to 4.16A12 depict the average characteristics and differences for the 10%, 40%, and 60% of least and most beneficiary adopters. The tables suggest that the estimates, together with trends, are qualitative similar to the 20%.

Furthermore, we test the sensitivity our baseline estimates to different model specifications by taking the log of net income of maize and legume yield and per capita food expenditure. Table 4.10A6 and Figure 4.6A2 report the average and distributional effects of adopting SI practices. The estimates, including the patterns, are qualitatively akin to our estimates in Table 4.2 and Figure 4.1.

4.5. Conclusions and policy implications

This paper examined the mean and heterogeneous effects of adopting SI practices on farmers' net income of maize and legume yield and household welfare. In addition, the study examined the heterogeneity in the treatment effect at the subpopulation of adopters as well as identified the adopters of the SI practices that benefited most and least from adoption. The study employed different estimators (e.g. 2SLS, Probit-2SLS, and IV-Lasso) in examining the average effects and used the instrumental variable quantile regression approach in examining the heterogeneous effects. The sorted effect method was also used to estimate the heterogeneous treatment effects at the subpopulation of adopters as well as identified the adopters that benefited most from adoption.

The results of our analysis indicated that, on average, the adoption of SI practices increased net income of maize and legume yield and per capita food expenditure of adopters. The findings also showed that the effects are highly heterogeneous across the farm households. The results imply that the effects at the subpopulation of adopters are very heterogeneous and that not all the adopters benefited from adoption. A classification analysis of the 20% adopters that benefited most and least from adoption based on the net income of maize and legume yield gap indicates that compared to the least beneficiary adopters, the most beneficiary adopters are more likely to live in highly resource endowed farm households (e.g. have more livestock and productive asset) with relatively younger household heads and fewer household members. They are also more likely to travel longer distances before reaching the nearest market and motorable road.

On the policy side, the study indicates that policies and programmes that aimed at improving farm households' crop productivity and welfare can be achieved through diffusion of SI practices. Our heterogeneity in the effect at the quantile level and the subpopulation of adopters echoes previous calls for examining effects beyond average (Bitler et al., 2006).

Furthermore, the study reveals that the differences in resource endowment of farmers account for the heterogeneity in the benefits associated with farmers' adoption of SI practices, suggesting the is need to target households during scaling up. Moreover, the findings at the subpopulation level suggest revision of current dissemination strategies during scaling up if crop productivity and household welfare of low resource endowed households are to be enhanced. The results further reveal the need for policymakers to move away from the assumption that "improved" agricultural technologies are inherently superior and non-adoption is the result of farmers' lack of knowledge, or exposure to technologies, and question whether households have the necessary resources to continue to adopt a given agricultural technology.

Finally, the findings suggest that programmes and policies targeted towards enhancement of farmers' adoption should not only aim at overcoming the immediate barriers to adoption through training and provision of inputs, but should also aim at sustaining adoption (Maggio et al., 2021). This would require the provision of support services. For example, social protection programmes in rural area that provide cash and in-kind support could be modified by targeting (e.g. farm households with large members) and linking the support to adoption of sustainable agricultural practices such as SI practices (Holden et al., 2006; Pannell et al., 2014; Sitko et al., 2021). This would require the involvement of key government ministries (e.g. social welfare) in the scaling up policy-decision making.

Appendix 4

Table 4.5 A1: Differences in the average characteristics of adopters and non-adopters of SI practices

Variable	Adopters		Non-adopters		Difference
	Mean	SD	Mean	SD	
Female	0.254	0.436	0.092	0.289	0.161**
Age	47.979	13.418	47.829	14.034	0.150
Household size	8.742	4.402	9.110	5.525	-0.368
Dependency ratio	1.036	0.667	1.123	0.747	-0.087
Livestock size	3.384	6.399	3.559	7.265	-0.175
Read and write	0.143	0.351	0.150	0.357	-0.007
Market	30.902	23.746	34.047	27.870	-3.145
Assets	8.199	5.792	8.513	7.016	-0.314
Farm size	0.987	0.750	1.880	2.163	-0.893**
Off farm income	0.697	0.460	0.728	0.446	-0.031
Norther region	0.334	0.473	0.633	0.483	-0.299**
Upper East	0.254	0.436	0.092	0.289	-0.035**
Upper West	0.411	0.493	0.275	0.447	0.136**
Extension services	0.986	0.117	0.538	0.499	0.448**
Group	0.275	0.447	0.116	0.321	0.109**
Female labour	26.035	19.646	44.820	42.420	-18.785**
Male labour	31.240	23.736	44.865	25.336	0.347**
Motorable road	5.916	8.334	6.531	13.457	-0.615
Outcome variable					
Net income of maize and legume yield	1446.652	2865.638	481.147	2787.624	965.505**
Per capita food expenditure	7.572	10.937	8.702	9.816	-1.130
Observations	287		327		

Note: 1UDS=GHS 5.4. The Mann-Whitney test and the Chi-square test were used to test for differences of the continuous and binary variables, respectively. SD denotes standard deviation.

Table 4.6A2: Test of instrument validity for net income of maize and legume yield and per capita food expenditure

Variable	Decision to adopt (1/0)	Net income of maize and legume yield (GHS/ha)	Per capital food expenditure (GHS)
Extension service	0.736*** (0.127)	328.221(265.055)	1.250 (0.866)
Group	0.263*(0.154)	202.737(301.835)	0.301(1.058)
Constant	-0.0172(0.473)	-301.835(862.758)	8.843***(3.214)
Wald test	χ^2= 183.88***	F-stat.= 1.49, p= 0.227	F-stat.= 1.24, p=0.290
R-squared	0.2167	0.052	0.154
Observations		614	

Note. Robust standard error in parentheses. *p<0.10, **0.05p<0.05, ***p<0.01. Estimates for the net income of maize and legume yield and per capita food expenditure were obtained with the ordinary least squares (OLS) model. For brevity, we did not report all the parameters. 1UDS=GHS 5.4 at time of survey.

Table 4.7A3: Test of instrument validity for maize yield and household income per month

Variable	Maize yield (kg/ha)	Household income per month (GHS)
Extension service	41.849(59.463)	238.059*(140.331)
Group	73.953(71.458)	-97.312(171.733)
Constant	863.962(212.775)	1805.859(513.168)
Wald test	F-stat.= 0.89, p= 0.4095	F-stat.= 1.45, p= 0.2350
R-squared	0.0502	0.0023
Observations		614

Note. Robust standard error in parentheses. *p<0.10, **0.05p<0.05, ***p<0.01. Estimates for the maize yield and household income were obtained using the ordinary least squares (OLS) model. For brevity, we did not report all the parameters. 1UDS=GHS 5.4 at time of survey.

Table 4.8A4: Matrix of correlation

Variable	Extension service	Group
Net income of maize and legume yield (GHS/ha)	0.077	0.081
Per capita expenditure (GHS)	0.098	0.030
Maize yield (kg/ha)	0.069	0.056
Household income per month (GHS)	0.047	-0.047

Note: None of the correlation estimate is statistically significant.

Table 4.9A5: Average effect of adopting SI practices on maize yield and household income

Estimator	Log maize yield (kg/ha)		Log household income per month (GHS)	
	Estimate	SE	Estimate	SE
2SLS	0.371	0.243	0.658**	0.344
Probit-2SLS	0.470*	0.251	0.690**	0.353
IV-Lasso	0.402**	0.204	0.542**	0.273
Observations			614	

Note. SE denotes robust standard error. *p<0.10, **0.05p<0.05, ***p<0.01. We note that the 2SLS and IV-Lasso account for homogeneous treatment effects, while the Probit-2SLS account for heterogeneous treatment effects

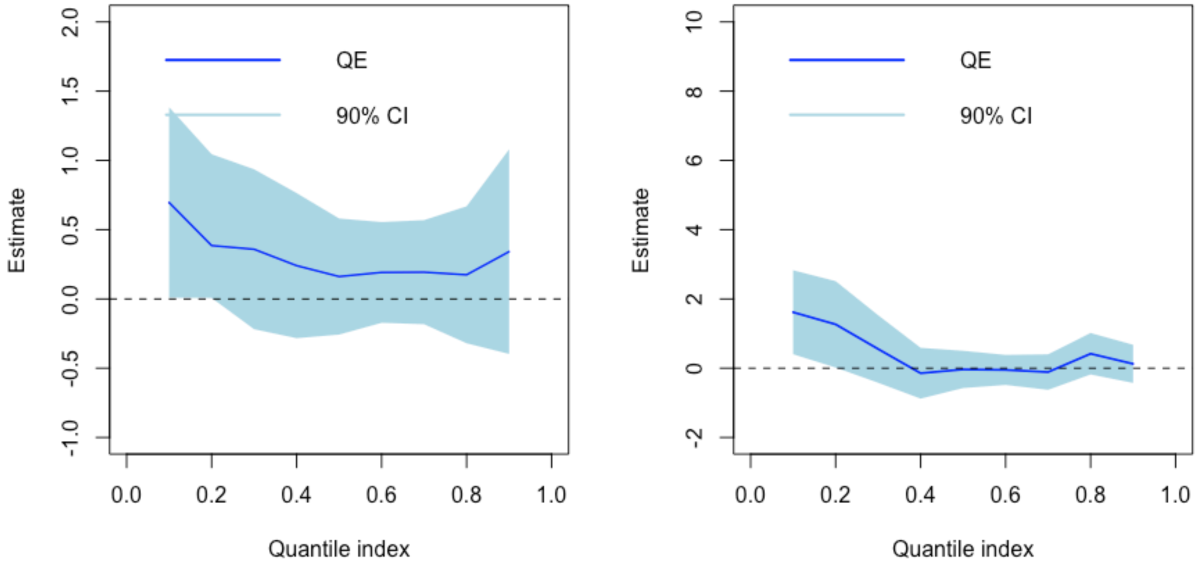

Figure 4.4A1: Distributional effects of adopting SI practices on log maize yield (left) and log household income per month (right). The 90% bootstrap confidence intervals were obtained with 300 repetitions Estimates were obtained using the instrumental variable quantile regression (IVQR) model approach.

Table 4.10 A6: Average effect of adopting SI practices on log net income of maize and legume yield and log per capita food expenditure

Estimator	Log net income of maize and legume yield (GHS/ha)		Log per capita food expenditure (GHS)	
	Estimate	SE	Estimate	SE
2SLS	6.956**	2.890	0.411	0.350
Probit-2SLS	7.569**	3.061	0.435	0.220
IV-Lasso	6.244**	2.475	0.809**	0.366
Observations			614	

Note. SE denotes robust standard error. *p<0.10, **0.05p<0.05, ***p<0.01. We note that the 2SLS and IV-Lasso account for homogeneous treatment effects, while the Probit-2SLS account for heterogeneous treatment effects

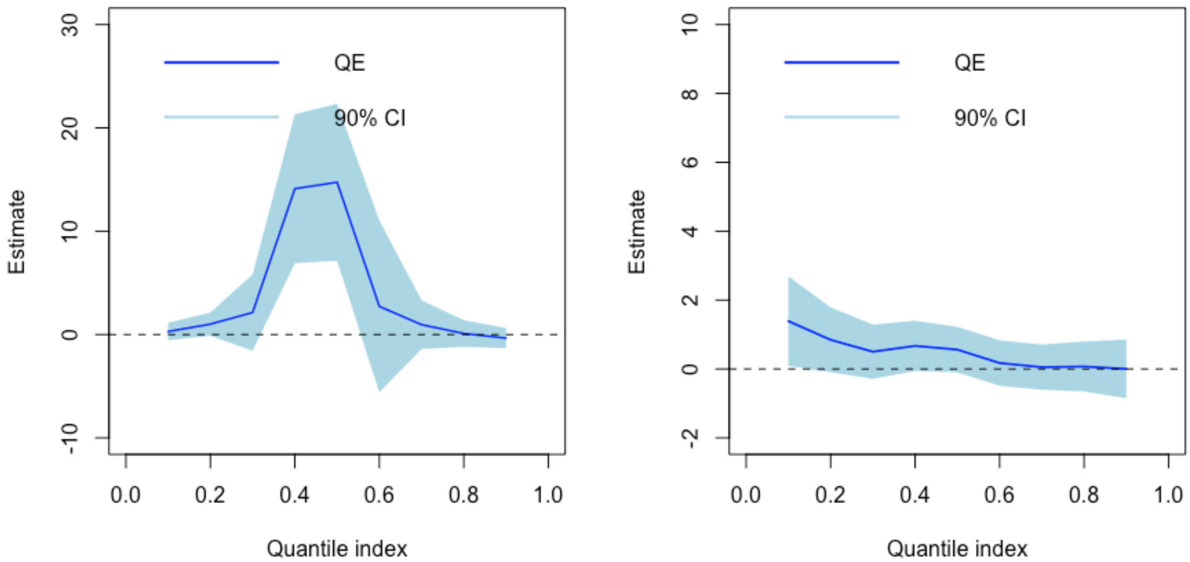

Figure 4.5A2: Distributional effects of adopting SI practices on log net income of maize and legume yield (left) and log per capita food expenditure (right). The 90% bootstrap confidence intervals were obtained with 300 repetitions. Estimates were obtained using the instrumental variable quantile regression (IVQR) model approach.

Table 4.11A7: Mean characteristics of the 10% least and most beneficiary adopters - classification analysis

Variable	Least	SE	Most	SE
Female	0.323	0.016	0.800	0.016
Male	0.677	0.016	0.200	0.016
Age	49.613	0.602	45.000	0.633
Household size	7.548	0.220	4.000	0.240
Dependency ratio	0.891	0.029	0.467	0.030
Read-write, no	0.935	0.015	0.400	0.015
Read-write, yes	0.065	0.015	0.600	0.015
Livestock size, log	0.935	0.015	0.400	0.015
Market, log	0.970	0.018	1.207	0.019
Asset, log	0.884	0.014	0.892	0.015
Farm size, log	0.283	0.008	0.208	0.009
Off-farm income, no	0.258	0.019	0.200	0.018
Off-farm income, yes	0.742	0.019	0.800	0.018
Northern region	0.000	0.023	0.200	0.022
Upper East region	0.000	0.018	0.800	0.017
Upper west region	1.000	0.021	0.000	0.019
Extension service, no	0.355	0.021	0.200	0.021
Extension service, yes	0.645	0.021	0.800	0.021
Group membership, no	0.968	0.015	0.000	0.017
Group membership, yes	0.032	0.015	1.000	0.017
Male labour, log	1.137	0.014	1.442	0.015
Female labour, log	1.306	0.013	1.187	0.014
Motorable	0.503	0.020	0.556	0.018
Net income of maize and legume yield	917.346	128.150	3245.960	126.128
Per capita food expenditure	3.129	0.422	62.525	0.420
Observations		614		

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions.

Table 4.12A8: Bias corrected difference in mean characteristics of the 10% least and most beneficiary adopters - classification analysis

Variable	Estimate	SE	P-value
Female	-0.477	0.008	0.420
Male	0.477	0.008	0.420
Age	4.613	0.294	0.000
Household size	3.548	0.098	0.000
Dependency ratio	0.424	0.015	0.000
Read-write, no	0.535	0.008	0.483
Read-write, yes	-0.535	0.008	0.483
Livestock size, log	-0.229	0.017	0.000
Market, log	-0.237	0.008	0.000
Asset, log	-0.237	0.008	0.000
Farm size, log	0.075	0.004	0.000
Off-farm income, no	0.058	0.009	0.600
Off-farm income, yes	-0.058	0.009	0.600
Northern region	-0.200	0.011	1.000
Upper East region	-0.800	0.008	0.373
Upper west region	1.000	0.011	1.000
Extension services, no	0.155	0.011	0.487
Extension services, yes	-0.155	0.011	0.487
Group membership, no	0.968	0.008	0.563
Group membership, yes	-0.968	0.008	0.563
Female labour, log	-0.305	0.008	0.000
Male labour, log	0.119	0.006	0.000
Motorable	-0.053	0.011	0.000
Net income of maize and legume yield	-2328.614	64.175	0.000
Per capita food expenditure	-59.396	0.177	0.000
Observations		614	

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions. The p-values are adjusted to control for joint testing of zero coefficients on all the covariates within the categories. The p-values for non-categories are for a single test.

Table 4.13A9: Mean characteristics of the 40% least and most beneficiary adopters - classification analysis

Variable	Least	SE	Most	SE
Female	0.628	0.015	0.881	0.016
Male	0.372	0.015	0.119	0.016
Age	48.244	0.526	45.966	0.520
Household size	8.640	0.227	7.644	0.210
Dependency ratio	0.942	0.027	1.181	0.027
Read-write, no	0.902	0.013	0.661	0.013
Read-write, yes	0.098	0.013	0.339	0.013
Livestock size, log	1.047	0.034	1.218	0.034
Market, log	1.282	0.018	1.484	0.019
Asset, log	0.809	0.014	0.820	0.013
Farm size, log	0.287	0.008	0.221	0.007
Off-farm income, no	0.323	0.018	0.203	0.017
Off-farm income, yes	0.677	0.018	0.797	0.017
Northern region	0.183	0.021	0.441	0.022
Upper East region	0.177	0.016	0.492	0.016
Upper west region	0.640	0.017	0.068	0.017
Extension service, no	0.293	0.020	0.186	0.021
Extension service, yes	0.707	0.020	0.814	0.021
Group membership, no	0.628	0.015	0.881	0.016
Group membership, yes	0.372	0.015	0.119	0.016
Male labour, log	1.331	0.015	1.382	0.014
Female labour, log	1.321	0.012	1.253	0.013
Motorable	0.577	0.018	0.536	0.018
Net income of maize and legume yield	1260.710	120.102	1819.554	126.496
Per capita food expenditure	4.624	0.430	16.980	0.422
Observations		614		

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions.

Table 4.14A10: Bias corrected difference in mean characteristics of the 40% % least and most beneficiary adopters - classification analysis

Variable	Estimate	SE	P-value
Female	-0.253	0.003	0.383
Male	0.253	0.003	0.383
Age	2.278	0.157	0.000
Household size	0.996	0.053	0.000
Dependency ratio	-0.239	0.007	0.000
Read-write, no	0.241	0.003	0.380
Read-write, yes	-0.241	0.003	0.380
Livestock size, log	-0.171	0.007	0.000
Market, log	-0.202	0.005	0.000
Asset, log	-0.010	0.003	0.001
Farm size, log	0.065	0.002	0.000
Off-farm income, no	0.120	0.005	0.377
Off-farm income, yes	-0.120	0.005	0.377
Northern region	-0.258	0.005	1.000
Upper East region	-0.315	0.004	1.000
Upper west region	0.572	0.006	0.597
Extension services, no	0.106	0.005	0.570
Extension services, yes	-0.106	0.005	0.570
Group membership, no	0.393	0.004	0.517
Group membership, yes	-0.393	0.004	0.517
Female labour, log	-0.051	0.003	0.000
Male labour, log	0.068	0.003	0.000
Motorable	0.041	0.005	0.000
Net income of maize and legume yield	-558.844	27.386	0.000
Per capita food expenditure	-12.356	0.106	0.000
Observations		614	

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions. The p-values are adjusted to control for joint testing of zero coefficients on all the covariates within the categories. The p-values for non-categories are for a single test.

Table 4.15A11: Mean characteristics of the 60% least and most beneficiary adopters - classification analysis

Variable	Least	SE	Most	SE
Female	0.711	0.016	0.902	0.015
Male	0.289	0.016	0.098	0.015
Age	48.500	0.532	47.626	0.528
Household size	9.026	0.230	8.878	0.207
Dependency ratio	0.998	0.027	1.160	0.027
Read-write, no	0.908	0.014	0.797	0.014
Read-write, yes	0.092	0.014	0.203	0.014
Livestock size, log	1.060	0.034	1.153	0.034
Market, log	0.549	0.018	0.507	0.018
Asset, log	0.824	0.013	0.842	0.013
Farm size, log	0.289	0.007	0.259	0.007
Off-farm income, no	0.329	0.017	0.276	0.017
Off-farm income, yes	0.671	0.017	0.724	0.017
Northern region	0.307	0.021	0.537	0.021
Upper East region	0.193	0.016	0.358	0.016
Upper west region	0.500	0.017	0.106	0.017
Extension service, no	0.259	0.020	0.179	0.020
Extension service, yes	0.741	0.020	0.821	0.020
Group membership, no	0.803	0.015	0.602	0.016
Group membership, yes	0.197	0.015	0.398	0.016
Male labour, log	1.381	0.014	1.448	0.014
Female labour, log	1.333	0.012	1.311	0.013
Motorable	0.549	0.018	0.507	0.018
Net income of maize and legume yield	1350.156	121.136	1694.575	129.024
Per capita food expenditure	5.138	0.406	11.504	0.391
Observations		614		

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions.

Table 4.16A12: Bias corrected difference in mean characteristics of the 60% least and most beneficiary adopters-classification analysis

Variable	Estimate	SE	P-value
Female	-0.192	0.002	0.377
Male	0.192	0.002	0.377
Age	0.874	0.102	0.000
Household size	0.148	0.036	0.000
Dependency ratio	-0.162	0.005	0.000
Read-write, no	0.111	0.002	0.390
Read-write, yes	-0.111	0.002	0.390
Livestock size, log	-0.093	0.005	0.000
Market, log	-0.112	0.003	0.000
Asset, log	-0.018	0.002	0.000
Farm size, log	0.029	0.001	0.000
Off-farm income, no	0.053	0.003	0.380
Off-farm income, yes	-0.053	0.003	0.380
Northern region	-0.230	0.003	1.000
Upper East region	-0.165	0.003	1.000
Upper west region	0.394	0.004	0.590
Extension services, no	0.080	0.003	0.567
Extension services, yes	-0.080	0.003	0.567
Group membership, no	0.201	0.003	0.507
Group membership, yes	-0.201	0.003	0.507
Female labour, log	0.02	0.00	0.000
Male labour, log	-0.07	0.00	0.000
Motorable	0.043	0.003	0.000
Net income of maize and legume yield	-344.420	18.405	0.000
Per capita food expenditure	-6.366	0.071	0.000
Observations		614	

Note. The estimates (PEs) are from a linear interactive model with interaction based on a quantile model. The standard errors were obtained using a weighted bootstrap with 300 repetitions. The p-values are adjusted to control for joint testing of zero coefficients on all the covariates within the categories. The p-values for non-categories are for a single test.

Chapter 5: Conclusions and policy implications

This study examined adoption and scaling up effects of disseminating sustainable intensification practices on farm performance and household welfare. More specifically, the study i) evaluated alternative ways of incentivising farmers into adopting sustainable intensification of agriculture practices (SI practices), ii) identified the farm households that need to be targeted during scaling-up, and iii) determined the farm households that benefited the most and least from SI adoption during diffusion.

To address the aforementioned research objectives, the study was framed within an agricultural development research programme in Ghana that aimed at improving farmers' crop productivity, farm incomes and food security through sustainably intensified farming system. Data used for the analysis was collected in 2019. Several econometrics methods were used in addressing the objectives of the study in each chapter of the thesis. The methods controlled for sample selection bias due to observed and unobservable factors.

Chapter 2 of the study examined alternative ways of inducing farmers into adopting agricultural technologies. The study employed the marginal treatment effect approach (MTE), the kernel matching and the inverse propensity score weighting with lasso regression (IPW-Lasso) in estimating the average effects of inducement on maize yield and net income of continuous induced and past induced farmers, respectively. The instrumental variable quantile regression method based on the control function approach was used in examining the heterogeneous effects of the inducement.

In chapter 3, the study on the whole identified the farm households that need to be targeted during scaling up SI practices. Specifically, the study adopted the redefined marginal treatment effect ($\widetilde{MTE}$) method in i) examining the effects of farmers resource endowment and unobserved factors on the marginal benefits of adopting SI practices, ii) estimating the heterogeneous effects of adopting SI practices on maize yield and net returns, and iii) predicting the farm households at the margin of adoption that need to be targeted at scale.

Finally, chapter 4 examined the average and distributional effects of adopting SI practices on farm performance and household welfare, especially at the subpopulation of adopters, as well as identified the farm households that benefited most and least from adoption. The study employed the 2SLS, the Probit-2SLS, and the IV-Lasso approaches in examining the effect of adopting SI practice on net returns of maize and legume yield and farm household welfare. The instrumental quantile regression method was employed in estimating the heterogeneous effects. Finally, the sorted treatment effect approach was used in estimating the heterogeneous treatment effects at the subpopulation of adopters, as well as identified the farm households that benefited most and least from adoption.

5.1. Summary of the results

The findings in chapter 2 revealed that the continuous inducement led to significant increases in maize yield and net income of continuous induced farmers. In contrast, estimates suggested that stopping the inducement would have led to about 64% and 53% decreased in maize yield and net income of continuous induced farmers, respectively. Distributional analysis indicated that the inducement effects are very heterogeneous across the quantile indexes. The analysis indicated that the inducement significantly impacted more on maize yield and net income of continuous induced farmers below the quantile indexes. In contrast, the distributional analysis revealed that past inducement had positive and significant effect on maize yield and net income of farmers at the lower quantile distribution. Furthermore, the results indicated that the continuous induced farmers benefited more from the inducement. Finally, a cost and benefit analysis showed that the inducement is somewhat more cost effective than a farmer field day.

The empirical analysis in chapter 3 suggested that the adoption of SI practices is influenced by information from extension services, group membership, household size, number of productive assets owned by the farm households and farm size. The findings also showed that both farmers' unobserved factors (e.g. managerial and technical skills) and resource endowment affected the marginal benefits of adopting SI practices. Point estimates imply that the adoption of SI practices increased farmers' maize yields and net returns. Estimates also suggested that both the marginal and average benefits of adopting SI practices are different. Scaling up policy analysis indicated that for all the potential scaling up policy options, scaling up SI practices to favour marginal farm household entrants who by observed socio-economic characteristics appear least likely to adopt would lead to the highest marginal benefits.

Finally, estimates in chapter 4 revealed that, on average, the adoption of SI practices increased net income from maize and legume production and per capital food expenditure of adopters. The findings also showed that the effects are highly heterogeneous across the farm households, and that the treatment effects at the subpopulation of adopters are heterogeneous. A classification analysis of the most and least beneficiary adopters based on the net income of maize and legume yield gap revealed that the adopters that benefited most are much more likely to live in highly resource endowed households (e.g. more livestock, productive asset, and access to labour) with relatively younger household heads and fewer household members. In addition, they are much more likely to travel longer distances before reaching the nearest weekly market and motorable road.

5.2. Policy implications

Findings of this study suggest that policies and programmes (e.g. SDG-2 of zero hunger of the United Nation) aimed at improving farm households' agricultural productivity and household welfare can be achieved through diffusion of SI practices. The study also indicates that the scaling up of SI practices should be aimed at farm households with the lowest probability of adoption based on observed socioeconomic characteristics. The study further implies that incorporating information about which farm households benefited most and least from adoption into scaling up policy decision-making can eschew mistargeting of agricultural technologies and practices.

The study also indicates the need for policy-makers to be cautious when using average estimates from piloted agricultural programmes for scaling up decision-making since the average estimates from piloted or on-station trials are always greater than average estimates at scale. In addition, the study implies that the diffusion of SI practices should not be an endgame but rather helping to sustain adoption is paramount since dis-adoption of agricultural technologies are pervasive in SSA after termination of most programme supports (Grabowski et al., 2016), and therefore the provision of support services such as strengthening of agricultural extension services, facilitation of farmers into cooperative groups and mechanization of agricultural operations can enhance the adoption of new agricultural technologies. Moreover, concerted collaborations between key government ministries (e.g. social welfare) and private business mechanization firms in scaling up decision-making can speed up the adoption of new agricultural technologies and practices.

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Appendix A

Ghana Africa RISING Follow-up Evaluation Survey - 2019

CONSENT FORM

My name is____and I work for a research programme, called Africa Research in Sustainable Intensification for the Next Generation -Africa RISING-, which aims to alleviate hunger and poverty by increasing agricultural productivity. Your household is one of the 700 households in the Northern, Upper East and Upper West Regions in Ghana selected to be interviewed now and at the end of the programme (after two years). Data collected from study households like yours will be used to determine and understand major constraints and opportunities for improving livelihood. Data to be collected from you will be coded and will be kept strictly confidential. All household identifying information will be held in strict confidence and used only for research purposes. No identifying information (e.g., respondent name) will appear in data report. Participation in this interview is voluntary and you may refuse to participate, discontinue the interview at any time, or skip any question you do not want to answer with no penalty or loss of benefits to which you are otherwise entitled. You are allowed to ask questions concerning the research, both before agreeing to participate in the interview, during, and after the interview.

As head of the household or spouse of the head, I would like to ask you questions mainly about agricultural activities and consumption. I will need to ask also other household members about health status and labour, as well as measure weight and height of all women of reproductive age and children under 5 years old. Answering these questions is expected to take around 3 hours in two visits. You may find some of the questions (for example about household asset ownership and consumption of food and non-food items) sensitive and you can refuse to answer any sensitive question without any consequence whatsoever.

Before I start, do you have any questions or is there anything I have said on which you would like further clarification? May I proceed with interviewing you and other household members?

Yes □ No □

Subject Name Subject Signature

Household location

A1	A2	A3	A4
Region	District	Community	Household
See codes	See codes	See codes	Enter 3-digit household code from the list of sampled households**

GPS coordinates

			Degree	Minute	Second
A5	GPS Latitude	N			
A6	GPS Longitude	W			
A7	Elevation (in meters)				

Survey Staff Details

A8	ENUMERATOR NAME:		
A9a	DATE OF INTERVIEW (FIRST VISIT): / / MM DD YYYY	(SECOND VISIT): / / MM DD YYYY	A9b
A10a	INTERVIEW STARTING TIME (FIRST VISIT): / HOUR MIN	(SECOND VISIT): / HOUR MIN	A10b
A11	NAME OF SUPERVISOR:		
A12a	DATE OF QUESTIONNAIRE INSPECTIONS BY SUPERVISOR:	1st inspection / /	2nd inspection / /

Household information

A13	Name of head of household	
A14	Name of respondent (if not head)	
A15	Relationship to head (if not head)	
A16	Was translator used? 1. Yes 2. No	
A17	Phone numbers (if available)	
A18	Religion of the head 1 Christian 2 Muslim 3 Traditional 4 Other 5 None	

08	Northern Region
Code	District name
12	Tolon-Kumbungu
13	Savelugu-Nanton
20	Mamprusi West

09	Upper East region
Code	District name
02	Kassena-Nankana West
03	Kassena-Nankana East
05	Talensi-Nabdam
06	Bongo

10	Upper West region
Code	District name
01	Wa West
02	Wa municipal
03	Wa East
05	Nadowli

Community codes	
Code	Village name
01	Arigu
02	Basigu
03	Bonia
04	Botingli
05	Cheyohi No. 2
06	Disiga
07	Duko
08	Fian
09	Gbanjon
10	Gia
11	Goli
12	Goripie
13	Goriyiri
14	Guo
15	Gushie
16	Gyilli
17	Issa
18	Jana
19	Kadia
20	Karemiga
21	Kpallung
22	Kpelung
23	Kpirim
24	Kukobila
25	Kukua
26	Laogri
27	Nabogu
28	Namiyila
29	Naro
30	Nasia
31	Natodori
32	Nyagli
33	Nyangua
34	Papu
35	Pase
36	Pigu
37	Sa Gie
38	Sabulungo
39	Shia
40	Siiriyin
41	Tabiase
42	Tanina
43	Tekuru
44	Tibali
45	Tiborgunayili
46	Tindan
47	Tingoli
48	Wogu
49	Yenduri
50	Zanko

Quantity unit codes*	
Code	Unit
01	Kilogram
02	Gram
03	Liter
04	Unit or Piece
05	Cane/Basket
06	Bucket
07	120 kg maxibag
08	100 kg maxibag
09	50kg minibag
10	Ox-cart
11	Trailer
12	Lorry
13	Headload
14	Bunch
15	Bale
16	Sachet/tube
17	Plate
18	Cup
19	Heap
20	Bowl
21	Other

Area unit codes*	
Code	Unit
01	Acre
02	Hectare
03	Meter squared (M2)
04	Football field
05	Other

Crop List	
Cereals	
11	Maize
12	Wheat
13	Pearl millet
14	Sorghum
15	Finger millet
16	Rice
19	Other cereals
Pulses and nuts	
21	Bean
22	Soybean
23	Pigeonpea
24	Chickpea
25	Cowpea
26	Peas
27	Groundnut
28	Bambara nuts
29	Other pulses, nuts
Vegetables	
31	Cabbage
32	Tomatoes
33	Okra
34	Amaranthus
35	Red pepper
36	Green pepper
37	Garden Eggs
38	Ayoyo
39	Bitter Leaves
40	Carrots
41	Watermelon
49	Other vegetables

Crop Varieties

Root and tuber crops	
51	Onion
52	Irish potato
53	Sweet potato
54	Garlic
55	Cassava
56	Ginger
57	Yam
59	Other roots, tubers
Perennial crops	
61	Avocado
62	Banana
63	Mango
64	Orange
65	Pawpaw/Papaya
66	Dawadawa
67	Oil palm
68	Sugar cane
69	Other perennial
Other crops	
71	Cotton
72	Baobab
73	Tobacco
74	Shea Nut
79	Other crops
Other land use	
81	Fallow
82	Pasture/grazing
83	Planted fodder
84	Planted trees
85	Natural trees
89	Other uses

Maize variety	
110	Obaatampa
111	Okomasa
112	Mamaba
113	Dadaba
114	Abelehi
115	Omankwa
116	Enii-Pibi
117	PANA\Hybrid
118	ETUBI\Hybrid
119	Aburohemaa
1101	Abrotia
1102	Golden Jubilee
1199	Other maize variety
Rice variety	
160	Marhal Perfume
161	Bouake 189
162	ITA 320
163	ITA 324
164	Togo Marshal
165	Jasmine 85
166	Torks
169	Other rice variety
Soyabean variety	
220	Enidaso
221	Jenguma
222	Soung-Pun
223	Sonda
224	Afayak
225	Salintuya 1
226	Songotra
227	Quarshie
229	Other bean variety

Cowpeas variety	
250	Zaayura
251	Paditua
252	Apagbaala
259	Others
Groundnut variety	
270	Chinese
279	Other groundnut variety
Tomato variety	
320	Roma
321	Manglo
329	Other tomato variety
Cassava Variety	
550	Sweet
551	Bitter
552	Ampong
553	Bankye Broni
554	Sika Bankye
555	Otuhia
559	Other cassava variety
Cotton Variety	
710	Stamp
711	FK37
719	Other cassava variety
Sweet Potato Variety	
430	Red
431	White
439	Other sweet potato variety

SECTION B. CHARACTERISTICS OF MEMBERS OF THE HOUSEHOLD*

INDIVIDUAL ID	ASK ALL HOUSEHOLD MEMBER. RESPONDENTS 12 OR OLDER SHOULD RESPOND RELEVANT QUESTIONS FOR THEMSELVES						14 YEARS OR OLDER	ONLY FOR MEMBERS 7 YEARS OR OLDER	
	Please tell me the names of all members of the household starting with the head of household.	What is the relationship of [NAME] to the head of household?	Is [NAME] male or female?	How old is [NAME]?		How many months of the past 12 months has [NAME] lived with the household?	What is [NAME]'s marital status?	What is the highest grade completed by [NAME]?	Which languages can [NAME] read and write?
	LIST ONLY NAMES OF HOUSEHOLD MEMBERS*	1 Head 2 Spouse 3 Son/daughter 4 Son/daughter in law 5 Grandchild 6 Parent or parent in law 7 Other related 8 Other unrelated	1 Male 2 Female	**[IF 6 YEARS AND 12 MONTHS OR OVER, GIVE YEARS ONLY. IF LESS THAN 6 YEARS AND 12 MONTHS, GIVE YEARS AND MONTHS]** **[PLEASE ASK BIRTH CERTIFICATE, ESPECIALLY FOR CHILDREN]**		1 Three months or more 2 Less than three months ▶ NEXT LINE	1 Monogamous married 2 Polygamous married 3 Living together 4 Separated 5 Divorced 6 Never married 7 Widow(er)	-1 No school/none 0 Kindegarten 1 Primary 1 2 Primary 2 3 Primary 3 4 Primary 4 5 Primary 5 6 Primary 6 7 JHS 1 8 JHS 2 9 JHS 3 10 Middle 11 SHS 1 12 SHS 2 13 SHS 3 14 SHS 4 15 O-LEVEL 16 A-LEVEL 17 TECHNICAL/TEACHER /COLLEGE/VOCA. 18 UNIVERSITY-DIPLOMA/ POLYTECHNIC 19 UNIVERSITY-DEGREE 20 POST-UNIVERSITY EDUCATION	1 Dagbani 2 Dagaare 3 Kasem 4 Gonja 5 Kusal 6 Likpakpa 7 Wali 8 Frafra 9 Multiple local languages 10 English 11 English and local language(s) 12 Other foreign languages 13 Cannot read and write 14 Don't know
				Years	Months				
ID	B1	B2	B3	B4a	B4b	B5	B6	B7	B8
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									
11									
12									

* The household is defined a s a group of people who share expenses and live and eat together most of the time, that is more than 3 months of the year or more than three days of the week.
A newborn less than 3 months has to be considered a household member

ISCO OCCUPATION CODE
1 Manager
2 Professional
3 Technician and associate professional
4 Clerical support worker
5 Service and sales worker
6 Skilled agricultural, forestry, and fishery workers
7 Craft and related trades worker
8 Plant and machine operator, and assembler
9 Elementary occupation
10 Armed forces
11 Other

ISIC BUSINESS SECTOR CODE
1 Agriculture, forestry and fishing
2 Mining and quarrying
3 Manufacturing
4 Electricity, gas, steam and air conditioning supply
5 Water supply; sewerage, waste management and remediation activities
6 Construction
7 Wholesale and retail trade; repair of motor vehicles and motorcycles
8 Transportation and storage
9 Accommodation and food service activities
10 Information and communication
11 Financial and insurance activities
12 Real estate activities
13 Professional, scientific and technical activities
14 Administrative and support service activities
15 Public administration and defence; compulsory social security
16 Education
17 Human health and social work activities
18 Arts, entertainment and recreation
19 Other

ASK THESE QUESTIONS ONLY FOR MEMBERS 7 YEARS OR OLDER																
INDIVIDUAL ID	What was the **primary** economic activity [NAME] was involved in during **the last 12 months**?	What is [NAME's] **occupation** in his/her primary economic activity?	What kind of **trade or business** is [NAME] engaged in his/her primary economic activity?	What was the **secondary** economic activity [NAME] was involved in during the last 12 months?	CHECK: WHAT ARE THE ANSWERS TO QUESTIONS B9 AND B11? 1 B9 AND/OR B11 IS 5, 6, OR 7 2 B9 AND B11 ARE BOTH NOT 5, 6, OR 7 ► B14	[ASK IF RESPONSE TO B9 AND/OR B11 IS 5, 6, OR 7] How much cash/in kind support did [NAME] receive in **total** (primary and secondary, if any) for paid work he did during the **last 12 months**? What period did the payment cover or is expected to cover? [FOR IN-KIND SUPPORT, ASK ESTIMATED VALUE] IF RESPONDENT HAS NOT YET BEEN PAID, ASK: How much cash would [NAME] expect to get paid? [PROBE RESPONDENT]		During the **last 12 months**, for how many months did [NAME] work on these activities? MAX AMOUNT: 12 MONTHS	**In those months that [NAME] worked**, how many weeks per month, on average, did [NAME] usually work on these activities? MAX AMOUNT: 4 WEEKS	**In those weeks [NAME] worked**, how many hours per week, on average, did [NAME] usually work on these activities? MAX AMOUNT: 168 HOURS	In the **last 7 days**, how many hours did [NAME] work on these activities? MAX AMOUNT: 168 HOURS WRITE 0 IF RESPONDENT DID NOT WORK IN THE LAST 7 DAYS ► NEXT LINE	Why was [NAME] not available for work during the **last 12 months**?	[ASK IF RESPONSES TO B18 IS 5,6,7] **During the last 12 months**, for how long was [NAME] unable to work as a result of an illness or injury? [WRITE 0 IF [NAME] **WAS ABLE** TO WORK ►NEXT LINE]		What type of illness, symptoms or injury did cause [NAME] to be unable to work? LIST UP TO TWO	
	1 Self-employed in agriculture without employees 2 Self-employed in agriculture with employees 3 Self-employed in non-agriculture-without employees 4 Self-employed in non-agriculture - with employees 5 Hired in agriculture 6 Hired in non-agriculture 7 Informal labor (paid) 8 Unpaid family helper in agriculture 9 Unpaid family helper in non-agriculture 10 Unavailable to work ► B18 11 Looking for work ► NEXT LINE	[SEE ISCO CODES ABOVE FOR OCCUPATION}	[SEE ISIC CODES ABOVE FOR BUSINESS SECTOR]	1 Self-employed in agriculture without employees 2 Self-employed in agriculture with employees 3 Self-employed in non-agriculture-without employees 4 Self-employed in non-agriculture - with employees 5 Hired in agriculture 6 Hired in non-agriculture 7 Informal labor (paid) 8 Unpaid family helper in agriculture 9 Unpaid family helper in non-agriculture 10 None		1 HOUR 2 DAY 3 WEEK 4 FORTNIGHT 5 MONTH	6 QUARTER 7 HALF YEAR 8 YEAR 9 OTHER 10 REFUSE TO ANSWER					1 In school ►NEXT LINE 2 Household duties ►NEXT LINE Unable to work: 3 Too young ►NEXT LINE 4 Too old ►NEXT LINE 5 Sick 6 Disabled 7 Other		1 Month 2 Week 3 Day	1 Fever 2 Malaria 3 Stomach Ache / Diarrhea 4 Headache 5 Heart 6 Lung 7 Maternity 8 Ulcer 9 Disability/accident 10 Other	
						GHC	UNIT	MONTHS	WEEKS	HOURS	HOURS		DURATION	UNIT	1ST	2ND
ID	**B9**	**B10a**	**B10b**	**B11**	**B12**	**B13a**	**B13b**	**B14**	**B15**	**B16**	**B17**	**B18**	**B19a**	**B19b**	**B20a**	**B20b**
1																
2																
3																
4																
5																
6																
7																
8																
9																
10																
11																
12																

SECTION B. CHARACTERISTICS OF MEMBERS OF THE HOUSEHOLD*

INDIVIDUAL ID	LIST ONLY NAMES OF HOUSEHOLD MEMBERS	1 Male 2 Female	Age Years
ID	B1	B3	B4a
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			

SECTION C: CHILD ANTHROPOMETRY

ENUMERATOR: ASK PARENTS/CAREGIVERS OF CHILDREN BETWEEN THE AGES OF 0-59 MONTHS.

	IS [NAME] 5 YEARS OR YOUNGER?	Has [NAME] had diarrhea in the last 3 months?	WAS [NAME] MEASURED?	WHY WAS [NAME] NOT MEASURED? 1 CURRENTLY NOT HOME 2 TOO ILL 3 UNWILLING 4 OTHER	Where does [NAME]'s MOTHER live? [IF MOTHER LIVES IN THE HOUSE, COPY HER HOUSEHOLD MEMBER ID. IF MOTHER DOES NOT LIVE INSIDE THE HOUSE, WRITE 97. IF MOTHER IS DEAD, WRITE 98. WRITE 99 IF NOT KNOWN]	Where does [NAME]'s FATHER live? [IF FATHER LIVES IN THE HOUSE, COPY HIS HOUSEHOLD MEMBER ID. IF FATHER DOES NOT LIVE INSIDE THE HOUSE, WRITE 97. IF FATHER IS DEAD, WRITE 98. WRITE 99 IF NOT KNOWN]	**WEIGHT** [IF LESS THAN 10 KG, PUT TWO LEADING ZEROS (8.5 kg=008.5). IF MORE THAN 10 KG AND LESS THAN 100 KG, PUT ONE LEADING ZERO (15.5 KG = 015.5 KG)]	**HEIGHT** [IF LESS THAN 100 CMS, PUT ONE LEADING ZERO (97.3 CM=097.3 CM)]	WAS HEIGHT / LENGTH MEASURED WITH CHILD STANDING OR LYING DOWN [LATTER ONLY FOR CHILDREN **LESS THAN 2 YEARS** OLD]?	**UPPER ARM CIRCUMFERENCE** [MEASURE THE **LEFT** ARM] [PUT ONE LEADING ZERO (3.5 CM=03.5 CM)]
	1 YES 2 NO ► NEXT LINE	1 YES 2 NO	1 YES ► C5 2 NO	►NEXT LINE			KG	CM	1 Standing 2 Lying down	CM
ID	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
1							___ . _	___ . _		__ . _
2							___ . _	___ . _		__ . _
3							___ . _	___ . _		__ . _
4							___ . _	___ . _		__ . _
5							___ . _	___ . _		__ . _
6							___ . _	___ . _		__ . _
7							___ . _	___ . _		__ . _
8							___ . _	___ . _		__ . _
9							___ . _	___ . _		__ . _
10							___ . _	___ . _		__ . _
11							___ . _	___ . _		__ . _
12							___ . _	___ . _		__ . _

SECTION D: WOMEN ANTHROPOMETRY

ENUMERATOR: ASK THESE QUESTIONS OF EACH WOMAN OF REPRODUCTIVE AGE (15-49 YEARS) IN THE HOUSEHOLD. GET WOMAN'S ID CODE FROM THE HOUSEHOLD ROSTER.

ONLY WOMEN 15-49 YEARS									
	In what year and month were you born? [IF YEAR IS NOT KNOWN, ENTER 9999. IF MONTH IS NOT KNOWN, ENTER -99] [SEE BACK OF FORM] YEAR	MONTH	Are you between 15 and 49 years old? 1 YES 2 NO	CHECK MODULE "B MEMBERS": IS THE RESPONDENT BETWEEN THE AGES OF 15 AND 49 YEARS? [IF THE INFORMATION IN D1a AND D1b CONFLICTS WITH INFORMATION IN MODULE B (B4a AND B4b), DETERMINE WHICH IS MOST APPROPRIATE] 1 YES 2 NO ► NEXT LINE	Are you currently pregnant or breastfeeding? 1 YES, PREGNANT ► NEXT LINE 2 YES, BREASTFEEDING 3 NOT PREGNANT 4 DO NOT KNOW	WAS [NAME] MEASURED? 1 YES ► D7 2 NO	WHY WAS [NAME] NOT MEASURED? 1 CURRENTLY NOT HOME 2 TOO ILL OR DISABLED 3 UNWILLING 4 OTHER	**WEIGHT IN KILOGRAMS: WEIGHT THE WOMAN** [IF LESS THAN 100 KG, PUT ONE LEADING ZERO (50.5 KG=050.5 KG)] KG	**HEIGHT IN CENTIMETERS: MEASURE THE WOMEN** [IF LESS THAN 100 CMS, PUT ONE LEADING ZERO (97.3 CM=097.3)] CM
ID	D1a	D1b	D2	D3	D4	D5	D6	D7	D8
1								___ ___ ___ . ___	___ ___ ___ . ___
2								___ ___ ___ . ___	___ ___ ___ . ___
3								___ ___ ___ . ___	___ ___ ___ . ___
4								___ ___ ___ . ___	___ ___ ___ . ___
5								___ ___ ___ . ___	___ ___ ___ . ___
6								___ ___ ___ . ___	___ ___ ___ . ___
7								___ ___ ___ . ___	___ ___ ___ . ___
8								___ ___ ___ . ___	___ ___ ___ . ___
9								___ ___ ___ . ___	___ ___ ___ . ___
10								___ ___ ___ . ___	___ ___ ___ . ___
11								___ ___ ___ . ___	___ ___ ___ . ___
12								___ ___ ___ . ___	___ ___ ___ . ___

SECTION E. AGRICULTURAL LAND

E1	Does your household engage in any agricultural activities (e.g farming, livestock)?	1 YES 2 NO (►"MODULE "OTHER INCOME" L)	
E2	When was your **last completed cropping season**?	1 2012 (APRIL 2012- DEC 2012) 2 2013 (APRIL 2013- DEC 2013)	

ENUMERATOR: ASK ABOUT PARCELS OF LAND USED BY THE HOUSEHOLD IN THE LAST COMPLETED SEASON, WHETHER OWNED BY THE HOUSEHOLD

Parcel id number	How large is the land area of [PARCEL] that your household use?		Does [PARCEL] belong to your household? 1 Yes, entirely 2 Yes, communal 3 No, we rent it from others ► E6a 4 No, we sharecrop in ► E7 5 No, we borrow at no cost ► E8	Did your household **farm** [PARCEL] during [LAST COMPLETED CROPPING SEASON] ?	[IF RENTED IN OR OUT] How much did your household receive/pay in rent for [PARCEL]? [IF RENTED OUT GO TO MODULE LIVESTOCK J1]		[IF SHARECROPPED IN OR OUT] What percentage of the harvest from [PARCEL] paid (in cash or in-kind)? [IF SHARECROPPED OUT GO TO MODULE LIVESTOCK J1]	How did your household use the land area in [PARCEL] during [LAST COMPLETED CROPPING SEASON]?		What was the main source of water for [PARCEL] during [LAST COMPLETED CROPPING SEASON]?
		Area unit 1 Acre 2 Hectare 3 M^2 4 Football field 5 Other		1 Yes ► E8a 2 No, left fallow ► E12 3 No, we rent it out to others 4 No, we share-crop it out ► E7 5 No, we lend it at no cost ► GO TO MODULE LIVESTOCK J1	Value in GHC [if in-kind, estimate value]	Time unit 1 Per month 2 Per season 3 Per year		1 Annual crops 2 Seasonal crops 3 Tree crops 4 Livestock 5 Wood lots 6 Other [LIST UP TO TWO]		1 Rain ► E12 2 Surface irrigation 3 Groundwater irrigation 4 A combination (rain and irrigation)
	Area	Unit				► E8a	Percent	1st	2nd	
ID	E3a	E3b	E4	E5	E6a	E6b	E7	E8a	E8b	E9
1							%			
2							%			
3							%			
4							%			
5							%			
6							%			
7							%			
8							%			
9							%			
10							%			

OR NOT

ENUMERATOR: ASK ABOUT PARCELS OF LAND USED BY THE HOUSEHOLD IN LAST COMPLETED SEASON, WHETHER OWNED BY THE HOUSEHOLD OR NOT

Parcel id number	What kind of irrigation do you use for [PARCEL]?	What is the main means of irrigating [PARCEL]?	What is the type of the soil on [PARCEL]?	What proportion of [PARCEL] has crusted soils?	What is the color of the soil of [PARCEL]?	What is the slope [PARCEL]?	When was the last time you experienced waterlogging problems on [PARCEL]? [WRITE 0 IF NEVER EXPERIENCED]	How long does it take to get to [PARCEL] from your house by the usual mode of transport (**one way in minutes**)	[GPS MEASUREMENT TO BE COLLECTED **FROM THE PARCEL CLOSEST TO THE HOMESTEAD]**
	1 Ground water 2 River diversion 3 Pond diversion 4 Shallow well 5 Deep well 6 Water harvesting 7 Water cans 8 Drip irrigation 9 Other	1 Electric pump 2 Diesel/fuel pump 3 Gravity 4 Threaded pumps 5 Other	1 Clay 2 Loam 3 Sand ► E14 4 Sand/loam 5 Silt 6 Other	Percent	1 Black 2 Brown 3 Red 4 Red/Brown 5 Grey/Brown 6 Grey	1 Flat 2 Terraced 3 Gentile slope 4 Moderate slope 5 Steep slope 6 Depression	1 JAN 2 FEB 3 MAR 4 APR 5 MAY 6 JUN 7 JULY 8 AUG 9 SEP 10 OCT 11 NOV 12 DEC	1 Adjacent to homestead 2 Less than 15 mins 3 15 -30 mins 4 30 - 60 mins 5 More than 1 hour [IF THE HOUSEHOLD IS AMONG THOSE FROM WHICH LAND AREA MEASUREMENT NEEDS TO BE COLLECTED, GPS MEASUREMENT MUST BE TAKEN AFTER THE ENUMERATOR COMPLETES <u>LIVESTOCK MODULE (MODULE J2)</u>]	PARCEL AREA (IN HECTARE)
ID	**E10**	**E11**	**E12**	**E13**	**E14**	**E15**	**E16**	**E17**	**E18**
1				%					
2				%					
3				%					
4				%					
5				%					
6				%					
7				%					
8				%					
9				%					
10				%					

SECTION F. CROP INPUTS (SOIL CONSE

ENUMERATOR: ENTER PLOT-LEVEL INFO			LAST COMPLETED CROPPING SEASON														
PARCEL NUMBER	How many plots does your household have in [PARCEL]?	PLOT NUMBER	How much fertilizer was used? [IF A COMBINATION OF FERTILIZERS IS USED, **QUANTITY** AND **VALUE** SHOULD REFER TO THE QUANTITY AND VALUE OF **ALL** FERTILIZERS USED]			What type of **other organic inputs** did you apply on [PLOT]? 1 Household waste 2 Mulch/compost 3 Wood 4 Crop residue from this farm 5 Crop residue from other farms 6 A combination of organic inputs 7 Other 8 None ► F14a	How much **other organic input** did you apply on [PLOT]? [IF MORE THAN ONE TYPE OF 'OTHER ORGANIC INPUT' IS USED, ENTER TOTAL QUANTITY OF OTHER ORGANIC INPUTS APPLIED]		How much of **other organic input** for [PLOT] was brought onto the farm from outside?	If you bought the **other organic input** for this [PLOT] how much did it cost in unit prices [EXPRESSED IN UNIT F13b]?	How many trees (herbs, shrubs, etc) does the household **currently** have on [PLOT]? [ENTER NUMBER]	How many trees have you planted on [PLOT] **within the past 2 years**? [ENTER NUMBER]	How many trees have you removed from [PLOT] **last year**? [ENTER NUMBER]	Do you have soil erosion on [PLOT]?	What types of measures are you using to control soil erosion on [PLOT]? [LIST UP TO THREE]		
[COPY PARCEL NUMBER FROM AGRICULTURAL MODULE. REPEAT PARCEL NUMBER IF THERE ARE MULTIPLE PLOTS ON THE PARCEL]	[FOR EACH PARCEL, WRITE THE NUMBER OF PLOTS]	[WRITE PLOT NUMBER]	Quantity	Unit [SEE PAGE CODE]	Total value GHC		Quantity	Unit [SEE PAGE CODE]	Quantity [WRITE 0 IF IT WAS ALL GENERATED ON-FARM AND ►F14a]	Unit price in GHC [IF OTHER ORGANIC INPUT IS OBTAINED FOR FREE OR IS COLLECTED WRITE 0]	[WRITE 0 IF NONE]	[WRITE 0 IF NONE]	[WRITE 0 IF NONE]	1 Yes 2 No ► NEXT LINE	1 Stone terraces 2 Fanya juu/chini 3 Other terrace 4 Grass strips/barriers (e.g. vetiver grass) 5 Drainage/ditches 6 Trash lines 7 Planting trees 8 Ripping 9 Contour bands 10 Marker ridges 11 Ditches/swales 12 Box ridges 13 Mulch 14 Other 15 None		
F1a	**F1b**	**F2**	**F11a**	**F11b**	**F11c**	**F12**	**F13a**	**F13b**	**F13c**	**F13d**	**F14a**	**F14b**	**F14c**	**F15**	**F16a**	**F16b**	**F16c**

* Leguminous trees are ones that add nitrog

Quantity unit codes*

Code	Unit
01	Kilogram
02	Gram
03	Liter
04	Unit or Piece
05	Cane/Basket
06	Bucket
07	**120 kg maxibag**
08	**100 kg maxibag**
09	**50kg minibag**
10	Ox-cart
11	Trailer
12	Lorry
13	Headload
14	Bunch
15	Bale
16	Sachet/tube
17	Plate
18	Cup
19	Heap
20	**Bowl**
21	Other

Area unit codes*

Code	Unit
01	Acre
02	Hectare
03	Meter squared (M2)
04	Football field
05	Other

Cereals

11	Maize
12	Wheat
13	Pearl millet
14	Sorghum
15	Finger millet
16	Rice
19	Other cereals
Pulses and nuts	
21	Bean
22	Soybean
23	Pigeonpea
24	Chickpea
25	Cowpea
26	Peas
27	Groundnut
28	Bambara nuts
29	Other pulses, nuts
Vegetables	
31	Cabbage
32	Tomatoes
33	Okra
34	Amaranthus
35	Red pepper
36	Green pepper
37	Garden Eggs
38	Ayoyo
39	Bitter Leaves
40	Carrots
41	Watermelon
49	Other vegetables

Root and tuber crops

51	Onion
52	Irish potato
53	Sweet potato
54	Garlic
55	Cassava
56	Ginger
57	Yam
59	Other roots, tubers
Perennial crops	
61	Avocado
62	Banana
63	Mango
64	Orange
65	Pawpaw/Papaya
66	Dawadawa
67	Oil palm
68	Sugar cane
69	Other perennial
Other crops	
71	Cotton
72	Baobab
73	Tobacco
74	Shea Nut
79	Other crops
Other land use	
81	Fallow
82	Pasture/grazing
83	Planted fodder
84	Planted trees
85	Natural trees
89	Other uses

Maize variety

110	Obaatampa
111	Okomasa
112	Mamaba
113	Dadaba
114	Abelehi
115	Omankwa
116	Enii-Pibi
117	PANA\Hybrid
118	ETUBI\Hybrid
119	Aburohemaa
1101	Abrotia
1102	Golden Jubilee
1199	Other maize variety
Rice variety	
160	Marhal Perfume
161	Bouake 189
162	ITA 320
163	ITA 324
164	Togo Marshal
165	Jasmine 85
166	Torks
169	Other rice variety
Soyabean variety	
220	Enidaso
221	Jenguma
222	Soung-Pun
223	Sonda
224	Afayak
225	Salintuya 1
226	Songotra
227	Quarshie
229	Other bean variety

Cowpeas variety

250	Zaayura
251	Paditua
252	Apagbaala
259	Others
Groundnut variety	
270	Chinese
279	Other groundnut variety
Tomato variety	
320	Roma
321	Manglo
329	Other tomato variety
Cassava Variety	
550	Sweet
551	Bitter
552	Ampong
553	Bankye Broni
554	Sika Bankye
555	Otuhia
559	Other cassava variety
Cotton Variety	
710	Stamp
711	FK37
719	Other cassava variety
Sweet Potato Variety	
430	Red
431	White
439	Other sweet potato variety

SECTION G1. CROP PRODUCTION

ENUMERATOR: FIRST ASK WHICH CROPS WERE GROWN BY THE HOUSEHOLD ON EACH PARCEL AND EACH PLOT THEN ASK G1_5A-G1_9. NOTE THAT INFORMATION TO BE COLLECTED IN THIS MODULE IS AT PARCEL-PLOT-CROP LEVEL FOR THE LAST COMPLETED CROPPING SEASON.

		LAST COMPLETED CROPPING SEASON									
Parcel number	Plot number [NUMBER WITHIN PARCEL]	What crop was planted on this plot?	STOP AND COMPLETE THE G CROP FLAP	What was the area planted with [CROP] on this plot?		What was the % of area planted with [CROP] on this plot? [PLAY THE "50 BEANS GAME" ONLY FOR MULTIPLE CROPS IN A PLOT. WRITE 100 IF SINGLE CROP PER PLOT]	How much [CROP] was harvested from this [PLOT]?		Which family member had **main responsibility** for farming this [PLOT]?	How was the yield of your household's harvest in [LAST COMPLETED CROPPING SEASON] compared to your household's harvest in a normal year?	What is the main reason for the difference in yield between [LAST COMPLETED CROPPING SEASON] and the same farming season in a normal year?
[COPY PARCEL ID NUMBER FROM MODULE "E LAND" AND REPEAT PARCEL NUMBER IF THERE ARE MULTIPLE PLOTS ON PARCEL]	[REPEAT PLOT NUMBER IF THERE ARE MULTIPLE CROPS ON PLOT]	CROP CODE [SEE ABOVE]		Area	Area unit 1 Acre 2 Hectare 3 M^2 4 Football field 5 Other	[ENTER **THE % OF AREA PLANTED (MULTIPLY THE NUMBER OF BEANS BY 2)** FOR EACH CROP IN AN INTERCROPPED PLOT]	Quantity	Unit [SEE PAGE CODE]	1 Head 2 Spouse of head 3 Both head and spouse 4 Other	1 Much higher 2 Little higher 3 Roughly the same ►NEXT LINE 4 Little lower 5 Much lower 6 Don't know►NEXT LINE	1 Good rainfall 2 Bad rain fall 3 Fertilizer use 4 Improved seed use 5 Use of chemicals (e.g., insecticides, weed killers) 6 Soil degradation 7 Pests or disease 8 Multiple reasons 9 Other
G1_1	**G1_2**	**G1_3**		**G1_4a**	**G1_4b**	**G1_5**	**G1_6a**	**G1_6b**	**G1_7**	**G1_8**	**G1_9**
						%					
						%					
						%					
						%					
						%					
						%					
						%					
						%					
						%					
						%					
						%					
						%					

Note: For mixed cropping or more than one crop in a plot, record plot number in more than one row and each crop in a separate row.

SECTION G2. CROP INPUTS (COSTS)

ENUMERATOR: COMPLETE G2_2a TO G2_7 FOR EACH CULTIVATED CROP IN THE LAST COMPLETED CROPPING SEASON.

CROP CODE	For [CROP] grown in [THE LAST COMPLETED CROPPING SEASON], how much [INPUT TYPE] did your household use?														
	INPUT TYPE														
[COPY CROP CODES FROM CROP FLAP]	..seed saved from the previous harvest [WRITE 0 IF NO SAVED SEED AND -99 IF VALUE IS NOT KNOWN]			...seed obtained for free or in barter. [WRITE 0 IF NO FREE/BARTER SEED AND -99 IF VALUE IS NOT KNOWN]			...traditional seed that was purchased. [WRITE 0 IF NO TRADITIONAL SEED IS PURCHASED AND -99 IF VALUE IS NOT KNOWN]			...improved seed that was purchased. [WRITE 0 IF NO IMPROVED SEED IS PURCHASED AND -99 IF VALUE IS NOT KNOWN]			...pesticides, herbicides [WRITE 0 IF NO PESTICIDES/HERBICIDES AND -99 IF VALUE IS NOT KNOWN]	...other non- labor expenses (e.g., crop residues, off-farm manure, animal or equipments rental cost) [WRITE 0 IF NO OTHER NON-LABOR EXPENSES AND -99 IF VALUE IS NOT KNOWN]
	Quantity	Unit [SEE PAGE CODE]	Estimated value	Quantity	Unit [SEE PAGE CODE]	Estimated value	Quantity	Unit [SEE PAGE CODE]	Value	Quantity	Unit [SEE PAGE CODE]	Value	Value	Value
			In GHC			In GHC			In GHC			In GHC	In GHC	In GHC
G2_1	G2_2a	G2_2b	G2_2c	G2_3a	G2_3b	G2_3c	G2_4a	G2_4b	G2_4c	G2_5a	G2_5b	G2_5c	G2_6	G2_7

*Basal application refers to an application of fertilizer near the base of the stems.

Note: Person-days are calculated as the number of workers times the number of days they worked. For example, if 5 people work for 3 days and 2 people continue for 6 more days, the total number of person-days is 5x3 + 2x6 = 27.

	Number of workers		Number of days worked by each worker		Person-days
land preparation -male		x		=	
land preparation -female		x		=	
planting -male		x		=	
planting -female		x		=	
fertilizing -male		x		=	
fertilizing -female		x		=	
weeding -male		x		=	
weeding -female		x		=	
harvesting -male		x		=	
harvesting- female		x		=	
other -male		x		=	
other- female		x		=	

SECTION G3. CROP INPUTS (LABOR)

ENUMERATOR: COMPLETE G3_2_1m TO G3_7b FOR EACH CULTIVATED CROP. WRITE 0 IF NO LABOR IS USED FOR [ACTIVITY] FOR [CROP]

CROP CODE	For the [CROP] grown in [LAST COMPLETED CROPPING SEASON] , how many person-days of **FAMILY, HIRED AND EXCHANGE LABOR** were used on [AGRICULTURAL ACTIVITY] ?												How much labor for [CROP] was family labor?	How much labor for [CROP] was exchange labor?	How much labor for [CROP] was hired labor?	Which percentage of labor for [CROP] was from females?	What was the average daily wage paid to <u>hired</u> laborer for [CROP]? [WRITE ESTIMATED VALUE IF PAID IN-KIND]	
[COPY CROP CODES FROM CROP FLAP]	land preparation (including harrowing & ridging)		planting		fertilizing		weeding		harvesting		other (i.e., spraying for pesticides, herbicides, weedicides)		1. All (100%) ► NEXT LINE 2. Most (~75%) 3. About half (~50%) 4. Some (~25%) 5. None (0%)	1. All (100%) ► NEXT LINE 2. Most (~75%) 3. About half (~50%) 4. Some (~25%) 5. None (0%)	1. All (100%) 2. Most (~75%) 3. About half (~50%) 4. Some (~25%) 5. None (0%) ► NEXT LINE	1. All (100%) ► G3_7b 2. Most (~75%) 3. About half (~50%) 4. Some (~25%) 5. None (0%)	Male	Female
	Person-days (Male)	Person-days (Female)	Person-days (Male)	Person-days (Female)	Person-days (Male)	Person-days (Female)	Person-days (Male)	Person-days (Female)	Person-days (Male)	Person-days (Female)	Person-days (Male)	Person-days (Female)					GHC per day	GHC per day
G3_1	**G3_2_1m**	**G3_2_1f**	**G3_2_2m**	**G3_2_2f**	**G3_2_3m**	**G3_2_3f**	**G3_2_4m**	**G3_2_4f**	**G3_2_5m**	**G3_2_5f**	**G3_2_6m**	**G3_2_6f**	**G3_3**	**G3_4**	**G3_5**	**G3_6**	**G3_7a**	**G3_7b**

G CROP FLAP

PARCEL NUMBER	PLOT NUMBER	CROP CODES
[COPY PARCEL NUMBERS FROM G1]	[COPY PLOT NUMBERS FROM G1]	[COPY CROP CODES FROM G1]

SECTION G4. CROP INPUTS (SEEDS)

ENUMERATOR: ASK G4_3 TO G4_10b FOR EACH CROP GROWN BY THE HOUSEHOLD.

		LAST COMPLETED CROPPING SEASON												
				........ASK THESE QUESTIONS ONLY IF G4_4=2, 3 OR 4 (I.E. IF USED SEED IS <u>NOT</u> FROM OWN HARVEST).........										
CROP NAME	CROP CODE	Did your household grow [CROP]? 1 Yes 2 No ►NEXT LINE	How much of the seed you used was saved from previous harvest? 1 All ►NEXT LINE 2 Small amount 3 Large amount 4 None	Where did you obtain the seed that was not saved from previous harvest? 1 Farmer 2 Grain trader 3 Input dealer 4 Cooperative 5 Extension service 6 NGO 7 Research institute 8 Seed company 9 Multiple sources 10 Other	How did you pay for this seed? 1 Free 2 Cash 3 Credit 4 Subsidy 5 Labor exchange 6 A combination 9 Other	How many minutes does it take to get to this supplier using the usual mode of transport? (one way in minutes) [WRITE - 99 if G4_5 = 9]	What was the name of the main variety of [CROP] seed used by your household? [LIST UPTO **THREE** MAIN VARIETIES, AND WRITE - 99 IF NAME OF SEED VARIETY IS NOT KNOWN]			Did you have any problems with this variety? [LIST UP TO **THREE** MAIN PROBLEMS] 1 Needs inputs 2 Low quality 3 Poor taste 4 Poor feed 5 Too costly 6 Can't save 7 Vulnerable to drought 8 Vulnerable to flooding 9 Poor straw 10 Shelf life 11 Poor germination 12 Multiple problems 13 Other 14 No problem			What are the **two** most important characteristics that the [CROP] seed variety should have? 1 Grain yield 2 Grain size 3 Disease/pest resistance 4 Drought tolerance 5 Flood tolerance 6 Low labor needs 7 Low input needs 8 Ease of processing 9 Market demand 10 Good taste 11 Good color 12 Fodder quality 13 Other	
							1st	2nd	3rd	1st	2nd	3rd	1st	2nd
G4_1	**G4_2**	**G4_3**	**G4_4**	**G4_5**	**G4_6**	**G4_7**	**G4_8a**	**G4_8b**	**G4_8c**	**G4_9a**	**G4_9b**	**G4_9c**	**G4_10a**	**G4_10b**
Maize	11													
Wheat	12													
Pearl millet	13													
Sorghum	14													
Finger millet	15													
Rice	16													
Bean	21													
Soyabean	22													
Pigeonpea	23													
Chick-peas	24													
Cow-peas	25													
Peas	26													
Groundnut	27													
Bambara nuts	28													
Cabbage	31													
Tomatoes	32													
Red pepper	35													
Green pepper	36													
Onion	51													
Irish potato	52													
Sweet potato	53													
Cassava	55													
Yam	57													
Cotton	71													

SECTION H. CROP SALES - QUANTITIES

ENUMERATOR: THIS TABLE IS AT THE CROP LEVEL, NOT PLOT LEVEL, FOR LAST COMPLETED CROPPING SEASON

What crops were grown during [LAST COMPLETED CROPING SEASON]? [COPY CROP CODES FROM MODULE G1 CROP CODE]	How much **failure** in [CROP] did you incur before the harvest?				What is the reason of the crop **failure**?	How much [CROP] **without stover was harvested** during [LAST COMPLETED CROPPING SEASON]?		How much stover of [CROP] was **harvested** during [LAST COMPLETED CROPPING SEASON]?		How much of the total harvest (including stover) was used for **animal feed**?			How much was left on the field as **crop residue (but not burned)?**			How much was **saved for seed** [LAST COMPLETED CROPPING SEASON]?		
	Quantity	Unit	Total estimated value	% of the usual harvest	1 Drought/little rain 2 Excessive rains/floods 3 Pests/diseases 4 Late planting 5 Poor quality soil 6 Multiple reasons 7 Other	Quantity [WRITE 0 IF NO HARVEST WITHOUT STOVER AND ► H5a]	Unit [SEE CODE PAGE]	Quantity [WRITE 0 IF NO HARVEST OF STOVER AND ► H6a]	Unit [SEE CODE PAGE]	Quantity [WRITE 0 IF NOT USED FOR ANIMAL FEED AND ► H7a	Unit [SEE CODE PAGE]	Estimated Value (GHC)	Quantity [WRITE 0 IF NO CROP RESIDU EAND ► H8a	Unit [SEE CODE PAGE]	Estimated Value (GHC)	Quantity [WRITE 0 IF SEED IS NOT SAVED ► H9a	Unit [SEE CODE PAGE]	Estimated Value (GHC)
	WRITE 0 IF NO CROP FAILUR E AND ►H4a	Unit [SEE CODE PAGE]	GHC	Percent														
H1	**H2a**	**H2b**	**H2c**	**H2d**	**H3**	**H4a**	**H4b**	**H5a**	**H5b**	**H6a**	**H6b**	**H6c**	**H7a**	**H7b**	**H7c**	**H8a**	**H8b**	**H8c**
				%														
				%														
				%														
				%														
				%														
				%														
				%														
				%														
				%														
				%														
				%														

ENUMERATOR: THIS TABLE IS AT THE CROP LEVEL, NOT PLOT LEVEL, FOR LAST COMPLETED CROPPING SEASON

What crops were grown during [LAST COMPLETED CROPING SEASON]? [COPY CROP CODES FROM MODULE G1 CROP CODE]	How much was used **for gifts and exchange** (except own consumption and sales)?			How much of the harvest was used for **own consumption**?		How much of the total harvest was used for **other purposes** (e.g., burned as crop residue, mulching, building material, used as firewood)		How much of this harvest was sold?		What unit price did you receive when selling this [CROP]?		Who in the household has the main responsibility for making sales-related decision on [CROP]? (e.g.,timing, amount, location)	What was the main place where this [CROP] was sold?	How long does it take you to go from your house to get to the main place where the [CROP] was sold (in minutes using the usual mode of transport)	Who was the **main** buyer of [CROP]?	Did the buyer contract you to grow [CROP]?
	Quantity [WRITE 0 IF NO GIFT/EXCHANGE ► H10a	Unit [SEE CODE PAGE]	Estimated Value (GHC)	Quantity [WRITE 0 IF NO OWN CONSUPTION ► H11a	Unit [SEE CODE PAGE]	Quantity [WRITE 0 IF NO OTHER USE ► H12a	Unit [SEE CODE PAGE]	Quantity [WRITE 0 IF NO SALE AND ► NEXT LINE]	Unit [SEE CODE PAGE]	GHC per quantity unit	Unit [SEE CODE PAGE]	1 Head 2 Spouse of head 3 Both head and spouse 4 Other	1 On farm or home ► H17 2 Local market 3 Regulated market 4 Roadside 5 Cooperative 6 Processor 7 Other	**TIME ONE WAY ONLY**	1 Farmer or consumer 2 Trader 3 Processor 4 Cooperative 5 Government 6 Other	1 Yes 2 No
H1	**H9a**	**H9b**	**H9c**	**H10a**	**H10b**	**H11a**	**H11b**	**H12a**	**H12b**	**H13a**	**H13b**	**H14**	**H15**	**H16**	**H17**	**H18**

SECTION I. CROP STORAGE

		Did you have any [CROP] in storage **one month after** [THE LAST COMPLETED CROPPING SEASON's] harvest?	What is the total quantity of [CROP] that you had in storage after [THE LAST COMPLETED CROPPING SEASON's] harvest, **excluding crop corpuses (stover)**?		What type of storage facility did you use to store [CROP]?	How much of the [CROP] you stored was lost before you could sell or consume it?	What was/is the main cause of these losses of [CROP]?	Which method do you use to dry [CROP]?	Do you know if Aflatoxin can affect [CROP] negatively? [ASK AT HOUSEHOLD LEVEL]
CROP CODE	CROP NAME	1 Yes 2 No ► NEXT LINE	Quantity	Unit [SEE CODE PAGE]	1 Granary 2 Community warehouse 3 Pit in ground 4 Drums 5 Cribs 6 Sacks/bags 7 Roof 8 Raised open platforms 9 Raised roofed platforms 10 Open ground-covered 11Open ground-uncovered 12 Underground 13 Commercial storage 14 Multiple methods 15 Other	Percent [WRITE 0 IF NONE AND ► I8]	1 Rodents 2 Insects 3 Mold 4 Theft 5 Harvested too early 6 Multiple reasons 7 Other	1 Piles of cobs/pods on the ground - **without** cover 2 Piles of cobs/pods on the ground - **with cover** 3 Dry, shell and dry 4 Dry and store 5 Lay on tarpaulin for sun drying 6 Dry at commercial facility 7 Not applicable 8 Other	1 Yes 2 No 3 Never heard of Aflatoxin 4 Don't know
I1	**I2**	**I3**	**I4a**	**I4b**	**I5**	**I6**	**I7**	**I8**	**I9**
11	Maize					%			
12	Wheat					%			
13	Pearl millet					%			
14	Sorghum					%			
15	Finger millet					%			
16	Rice					%			
21	Bean					%			
22	Soyabean					%			
23	Pigeonpea					%			
24	Chick-peas					%			
25	Cow-peas					%			
26	Peas					%			
27	Groundnut					%			
28	Bambara nuts					%			
52	Irish Potato					%			
53	Sweet potato					%			
55	Cassava					%			
57	Yam					%			
71	Cotton					%			

SECTION J1. LIVESTOCK OWNERSHIP

ASK THE HOUSEHOLD HEAD OR OTHER KNOWLEDGEABLE MEMBER

							Over the past 12 months...									
CODE	ANIMAL TYPE	**In the past 12 months**, have members of your household raised or produced [ANIMAL TYPE]?	What type of management system does the household use for [ANIMAL TYPE]?	Which family member had main responsibility for taking care of the [ANIMAL TYPE]?	How many [ANIMAL TYPE] does your household currently own?	What is the estimated **total value** of all [ANIMAL TYPE] your household currently own?	...how many [ANIMAL TYPE] have been **slaughtered** to be consumed in the household?	...how many [ANIMAL TYPE] were **born**?	...how many [ANIMAL TYPE] were **bought**?	...how many [ANIMAL TYPE] were **given as gift** (i.e., dowry, rite) or **stolen**?	...how many [ANIMAL TYPE] did you **lose due to illness**?	...how many of your [ANIMAL TYPE] have you **sold**? [WRITE 0 IF NONE AND ► J1_15a]	...on average, how much was the **unit price** of each of [ANIMAL TYPE] (or carcasses) sold?	...how much have you earned in total from the following [ACTIVITY]? [WRITE 0 IF NONE]	
		1. Yes 2. No ►NEXT LINE IF RESPONDENT DOES NOT HAVE ANY OF THE ANIMAL TYPES LISTED ►END OF FIRST VISIT	1.Grazing/open air only 2.Intensive/Caging only 3. Mixed	1 Head 2 Spouse of head 3 Both head and spouse 4 Other	Number	GHC total	Number	Number	Number	Number	Number	Number	GHC per animal	Activity	GHC total
J1_1	J1_2	J1_3	J1_4	J1_5	J1_6	J1_7	J1_8	J1_9	J1_10	J1_11	J1_12	J1_13	J1_14	J1_15a	J1_15b
100	Draught cattle													Rental/Cart	
101	Bulls -local-													Rental/Cart	
102	Bulls -improved-													Rental/Cart	
103	Fattening cattle -local-													Meat products	
104	Fattening cattle -improved-													Meat products	
105	Cows -local-													Dairy products	
106	Cows -improved-													Dairy products	
107	Heifers -local-														
108	Heifers -improved-														
109	Calves -local-														
110	Calves -improved-														
111	Horse/donkey/mule													Rental/Cart	
112	Goats -local-													Goat milk	
113	Goats -improved-													Goat milk	
114	Sheep													Wool/skins/milk	
115	Pigs -local-														
116	Pigs -improved-														
117	Chickens													Egg sales	
118	Fish														
119	Other livestock														
120	Honey bees*				*	*						*	*	Honey/Wax sales	

* Note: For honey bees, record number of occupied hives (not bees) in J1_6, J1_8, J1_10, J1_13; total value of hives in J1_7; and value per hive in J1_14.

SECTION J2. LIVESTOCK FEED
ASK THE HOUSEHOLD HEAD OR OTHER KNOWLEDGEABLE MEMBER

CODE	ANIMAL CATEGORY	Over the last 12 months...																
		...have members of your household raised or produced [ANIMAL CATEGORY]?	...how much labor time did your household spend on [ANIMAL CATEGORY]?		...how much labor time from hired workers was spent on [ANIMAL CATEGORY]?		...which percentage of the hired labor was females?	...what was the source of feed for [ANIMAL CATEGORY]?	...which of the following feed for [ANIMAL CATEGORY] have you used? [LIST UP TO THREE SOURCES]			...how much did you pay for feed for [ANIMAL CATEGORY]?	...how much feed for [ANIMAL CATEGORY] have you used **per day**, on average? [ESTIMATE GHC PER UNIT IF FEED WAS NOT PURCHASED, WRITE 0 IF NOT PURCHASED]					
			duration [WRITE 0 IF NO HOUSEHOLD LABOR]	1 Days 2 Weeks 3 Months	duration [WRITE 0 IF NO HIRED LABOR ► J2_6]	1 Days 2 Weeks 3 Months	1 All (100%) 2 Most (~75%) 3 About half (~50%) 4 Some (~25%) 5 None (0%)	1 Off farm (purchased) 2 Off-farm (non-purchased) 3 On-farm 4 Multiple sources	1 Crop residue 2 Green forages 3 Grazing/open air ► J2_11 4 Concentrate feeds 5 Legumes, fodder trees, shrubs 6 Multiple 7 Other			[WRITE 0 IF THERE WAS NO PURCHASE OF FEED]	Rainy season (April-November)			Dry season (December-May)		
		1. Yes 2. No ► NEXT LINE	number	Unit	number	Unit	%		1st	2nd	3rd	GHC	Quantity per day	Unit [SEE CODE PAGE]	GHC per unit	Quantity per day	Unit [SEE CODE PAGE]	GHC per unit
ID	**J2_1**	**J2_2**	**J2_3a**	**J2_3b**	**J2_4a**	**J2_4b**	**J2_5**	**J2_6**	**J2_7a**	**J2_7b**	**J2_7c**	**J2_8**	**J2_9a**	**J2_9b**	**J2_9c**	**J2_10a**	**J2_10b**	**J2_10c**
81	Large ruminants (cattle)																	
82	Equines (e.g., horses, donkeys, and mule)																	
83	Small ruminants (e.g. sheep, goats)																	
84	Chickens and poultry																	
85	Pigs																	

CODE	ANIMAL CATEGORY	Over the last 12 months...										
		...how frequently did your household face **shortage of drinking water** for [ANIMAL TYPE]?	...how much **manure did** [ANIMAL TYPE] produced that the household was able to collect?		...where did your household store **manure** coming from [ANIMAL TYPE]?	...for how many weeks have you stored manure coming from [ANIMAL TYPE]?	...which was the **main** use of this manure coming from [ANIMAL TYPE]?	...how much have you earned in total from **manure sales** by [ANIMAL TYPE]? [WRITE 0 IF NO SALE OF MANURE OR -99 IF DON'T KNOW]	...how much have you spent in total on costs for [ANIMAL TYPE] such as veterinary supplies, taxes, and hired labor?	...did [ANIMAL TYPE] receive supplemental feeds?	...how many **days** did [ANIMAL TYPE] graze **off farm**? [WRITE 0 IF [ANIMAL TYPE] DID NOT GRAZE OFF FARM ► NEXT LINE]	...when [ANIMAL TYPE] grazed **off farm**, on average for how many **hours** did the [AMINAL TRYPE] graze? [MAXIMUM VALUE SHOULD BE 24 HOURS]
		1 Always 2 Often 3 Sometimes 4 Rarely 5 Never	WRITE 0 IF NO MANURE WAS COLLECTED ► J2_17]		1 Stored open 2 Roofed 3 Sealed 4 Other 5 No storage ► J2_15		1 Recycled in the field 2 Sold 3 Source of energy 4 Plastering 5 Multiple uses 8 Other 7 None			1 Yes 2 No		
			Quantity	Unit [SEE CODE PAGE]		total weeks		GHC total	GHC total		total days	hours per day
ID	J2_1	J2_11	J2_12a	J2_12b	J2_13	J2_14	J2_15	J2_16	J2_17	J2_18	J2_19	J2_20
81	Large ruminants (cattle)											
82	Equines (e.g., horses, donkeys, and mule)											
83	Small ruminants (e.g. sheep, goats)											
84	Chickens and poultry											
85	Pigs											

ENUMERATOR: PLEASE THANK THE RESPONDENT AND SET UP DATE AND TIME FOR NEXT VISIT

CHECKLIST

G1_6. HAVE YOU DONE THE "50 BEANS GAME" TO CALCULATE INTERCROPPED AREA? QUESTION G1_6 IN CROP PRODUCTION SECTION G1
1 Yes
2 No
3 Household does not have intercropped plots

E18. IS THIS HOUSEHOLD AMONG SUB SAMPLE OF HOUSEHOLDS CHOSEN FOR COLLECTION OF LAND AREA MEASUREMENT? QUESTION E18 IN E LAND SECTION
1 YES [IF YES, PLEASE GATHER LAND AREA MEASUREMENT BY GOING TO THE PARCEL CLOSEST TO THE HOMESTEAD]
2 No

	END TIME	
A10c	:	
	HOUR	MIN

SECTION K. INTERACTION WITH AGRICULTURAL EXTENSION AGENTS AND AFRICA RISING

ASK THE HEAD OF THE HOUSEHOLD OR OTHER KNOWLEDGEABLE MEMBER

Source ID	Source Name	Have you received advice/information on vegetable gardens, crops, livestock, or soil and natural resource management from [SOURCE] in the last 12 months? 1 Yes 2 No ► NEXT LINE	Is [SOURCE] among the three most important sources you would prefer to ask/seek advice/information? 1 Yes, 1st most important 2 Yes, 2nd most important 3 Yes, 3rd most important 4 Not among the three important sources	During the last cropping season, how often did [SOURCE] have interaction with you to exchange advice on farming/raising livestock? 1 At least once a week 2 Not weekly but at least once a month 3 Not every month but at least once during the cropping season 4 Just once 5 Never 6 Other
ID	K1	K2	K3	K4
1	Friend/neighbor			
2	Model farmer			
3	Other farmer			
4	Farmer's group			
5	Agricultural development/ extension agent			
6	None			

K5	How far is your local Farmer Training Center (one way in minutes) using the usual mode of transport? [WRITE -98 IF DO NOT KNOW IF THERE IS ONE ►K7] [WRITE -99 IF DO NOT KNOW THE DISTANCE] ____ min
K6	Have you ever participated in the activities of your Farmer Training Center? 1 Yes 2 No
K7	Think of the agricultural extension/development agent you interact with the most. How long have you known that agent? [WRITE NUMBER OF YEARS, PUT 0.5 IF LESS THAN 1] [WRITE -99 IF DON'T KNOW ANY AGENT] ____ years
K8	Have you tried any new agricultural technologies/management practices during the last farming season? 1 Yes 2 No ►K10
K9	Have these been new activities your agent has demonstrated to you? 1 Yes 2 No
K10	Are you a member of your community's farmer research group? 1 Yes 2 No ►K12 3 NOT APPLICABLE
K11	Have you ever used a new technology that you have seen at your research group activity or field day? 1 Yes 2 No [WRITE -99 IF NOT APPLICABLE]
K12	Have you/your household ever participated in any group that focuses on the conservation of natural resources? 1 Yes 2 No
K13	Do you/your household currently participate in any social organization? 1 Yes 2 No
K14	Are you/your household satisfied with quantity, quality and timeliness of extension and input supply services? 1 Yes 2 No
K15	Have you heard of Africa RISING program? 1 Yes 2 No ► GO TO OTHER INCOME MODULE L
K16	Have you ever participated in any activity as part of/organized by Africa RISING program? 1 Yes 2 No ►K19
[K17]	Which Africa RISING-related activity did you get involved in? [LIST UP TO THREE] 1 Community meetings 2 Trainings 3 On-farm experimentation of new or improved agricultural technology 4 Demonstration field days 5 Other 1st K17a 2nd K17b 3rd K17c
K18	Do you plan to continue participating in Africa RISING activities in the next planting season (MAY 2014- DEC 2014)? 1 Yes ► GO TO OTHER INCOME MODULE L 2 No
[K19]	What are your reasons for not participating in Africa RISING activities? [LIST UP TO THREE] 1 Not relevant to my activities 2 Technology not appropriate 3 Too expensive 4 Too risky 5 Prefer to be on my own 6 Not enough information 7 No time 8 I was turned down 9 Other 1st K19a 2nd K19b 3rd K19c

SECTION L. OTHER INCOME
ASK THE HEAD OF THE HOUSEHOLD OR OTHER KNOWLEDGEABLE MEMBER

OTHER INCOME ACTIVITY CODE	OTHER INCOME ACTIVITY NAME	**In the past 12 months,** have members of your household received any income from [ACTIVITY]?	Who in the household is **mainly** responsible for [ACTIVITY]?	How many months **out of the past 12 months** did members of this household receive income from [ACTIVITY]?	For each of these months that your household earned income from [ACTIVITY], how much **MONTHLY INCOME**, on average, did your household make?	How important was [ACTIVITY] to meeting household expenses?
		1 Yes 2 No ► NEXT LINE	1. Head 2. Spouse of head 3. Both head and spouse 4. Other	Months	GHC per month	1 Very important 2 Important 3 Somehow important 4 Not very important
ID	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**
100	Family/Household non-farm enterprise income					
101	Firewood & other forest products (excluding charcoal)					
102	Sale of charcoal					
103	Sale of wild foods/bushmeat					
104	Grain milling					
105	Local beer brewing & malting					
106	Other agricultural processing business* (e.g., packaging)					
107	Pension					
108	Remittances from family members or friends					
109	Other assistance					
110	Property non-farm rental incomes (e.g., houses, tractors)					

* "Agricultural processing" includes processing of crops grown on farm and processed for sale

SECTION M. CREDIT

ENUMERATOR: ASK THE HOUSEHOLD HEAD OR OTHER KNOWLEDGEABLE MEMBER

M1	**During the last 12 months,** did anyone in this household apply for credit or ask for a loan of at least 50 GHC?	1 Yes 2 No ►M3	
M2	**During the last 12 months**, did the household receive a loan?	1 Yes 2 No	
M3	**During the last 12 months**, did the household receive any crop inputs or agricultural equipment on credit?	1 Yes 2 No ►HOUSING MODULE N	

ENUMERATOR: FOR EACH CROP INPUT OR EQUIPMENT RECEIVED ON CREDIT, FILL IN ONE LINE

		Did the household obtain [INPUT TYPE] on credit during the last 12 months?	Who offered the hosehold INPUT TYPE] on credit?	What was the value of [INPUT TYPE]?	How much time is the credit for this [INPUT TYPE] for?
INPUT CODE	INPUT TYPE NAME	1 Yes 2 No►NEXT LINE	1 Input supplier 2 Trader 3 Processor 4 Cooperative 5 Farmer 6 Min of Agric. 7 NGO 8 Multiple sources 9 Other	GHC	Months
ID	**M4**	**M5**	**M6**	**M7**	**M8**
1	Seed				
2	Fertilizer				
3	Pesticides*				
4	Farm machinery				
5	Animals				
6	Other input				

* It includes insecticides, herbicides, fungicides, etc.

SECTION N. HOUSING AND ASSETS

ASK THE HEAD OF THE HOUSEHOLD OR OTHER KNOWLEDGEABLE MEMBER

What is the <u>main</u> material used for the outer walls of the house? **N1**

1 Mud/mud brick/clay
2 Wood/bamboo
3 Stone/burned bricks
4 Cement/sandcrete bloc
5 Thatch/cardboard
6 Corrugated metal
7 Other

What is the <u>main</u> material used for the floor in your house? **N2**

1 Earth/mud/mud brick
2 Wood
3 Stone
4 Cement/concrete
5 Ceramic/tiles
6 Other

What is the <u>main</u> material used for the roof on your house? **N3**

1 Leaves/raffia/thatch
2 Wood
3 Corrugated metal
4 Cement/concrete
5 Asbestos/slate/tiles
6 Mud/earth roof (tembe)
7 Plastic sheeting
8 A combination
9 Other

How many distinct rooms does the household occupy located in the same or different places? (number) (exclude toilet, kitchen, & bath rooms) **N4**

How many external windows and doors does the housing unit have? **N5**

How much monthly rent are you paying if renting in, or how much monthly rent would you receive if you were to rent out this house? (GHC/MONTH) [ENTER -99 IF RESPONDENT DOES NOT KNOW] **N6**

What is the <u>main</u> source of drinking water for your household? **N7**

1 Piped into dwelling
2 Public tap
3 Borehole, well & pump
4 Well without pump
5 Spring
6 Pond/Lake/Dam
7 River
8 Rainwater
9 Sachet or bottled water
10 Other

What is the <u>main</u> type of toilet used by your household? **N8**

1 Private KVIP
2 Shared KVIP
3 Private latrine
4 Shared latrine
5 Bush or field
6 Other

What is the <u>main</u> type of lighting used by your household? **N9**

1 Electric lights
2 Torch
3 Candles
4 Oil or kerosene lamp
5 Solar panel
6 Other
7 None

What is the <u>main</u> type of cooking fuel used by your household? **N10**

1 Wood
2 Charcoal
3 Gas/LPG
4 Electricity
5 Kerosene/paraffine
6 Other

How many headloads of firewood do family members collect per day? [WRITE 0 IF NO FIREWOOD IS COLLECTED] **N11**

During the <u>last 12 months</u>, do you have to walk farther to gather enough firewood? **N12**

1 Yes
2 No

SECTION N. HOUSING AND ASSETS

ASK THE HEAD OF THE HOUSEHOLD OR OTHER KNOWLEDGEABLE MEMBER. READ ALOUD EACH ASSET TYPE.

ASSET CODE	HOUSEHOLD ASSET TYPE	How many units of [HOUSEHOLD ASSET TYPE] does your household currently own? [WRITE 0 IF NONE ► NEXT LINE]	When did your household acquire [HOUSEHOLD ASSET TYPE]? [WRITE FOUR DIGIT YEAR AND -99 IF DO NOT REMEMBER. IF MULTIPLE PIECES OF AN ASSET ARE ACQUIRED AT DIFFERENT TIMES, WRITE YEAR OF THE MOST RECENT PURCHASE]	How much did you pay for [HOUSEHOLD ASSET TYPE]? [WRITE 0 IF ITEM WAS OBTAINED FOR FREE]
ID	N13	N14	N15	N16
100	Improved charcoal/wood stove			
101	Kerosene stove			
102	Gas stove			
103	Wooden bed - modern			
104	Metal bed - modern			
105	Sofa chair			
106	Modern chair			
107	Modern table			
108	Radio			
109	Television			
110	Electric fan			
111	Refrigerator			
112	Land-line phone			
113	Mobile phone			
114	Bicycle			
115	Motorbike			
116	Car or truck			
117	Satellite dish			
118	Solar panel			
119	Wooden cabinets			
120	CD/DVD Player			

SERVICE CODE	SERVICE TYPE	How long does it take to get to [SERVICE TYPE], from your house, using the usual forms of transport? **[one way in minutes]** [ENTER -99 IF NOT APPLICABLE]
ID	N13	N17
300	the nearest motorable road?	
301	the nearest all-season road?	
302	the nearest asphalt road?	
303	the nearest weekly market place?	
304	the nearest daily market place?	
305	the district capital?	
306	the nearest place with daily bus stop or taxi	
307	the nearest health care facility?	
308	primary school?	
309	secondary school?	

Asset code	Farm asset type	How many units of [FARM ASSET TYPE] does your household currently own? [WRITE 0 IF NONE ► NEXT LINE]	When did your household acquire [FARM ASSET TYPE]? [WRITE FOUR DIGIT YEAR AND -99 IF DO NOT REMEMBER. IF MULTIPLE PIECES OF A FARM ASSET ARE ACQUIRED AT DIFFERENT TIMES, WRITE YEAR OF THE MOST RECENT PURCHASE]	How much did you pay for [FARM ASSET TYPE]? [WRITE 0 IF ITEM WAS OBTAINED FOR FREE]
ID	N13	N14	N15	N16
200	Cutlass			
201	Axe/pick-axe			
202	Sprayer			
203	Sickle			
204	Ox-plough			
205	Yoke			
206	Harrow			
207	Shovel			
208	Hoe			
209	Winnower			
210	Animal cart			
211	Power tiller			
212	Tractor			
213	Disc Plough			
214	Ox-ridger			
215	Ripper			

SECTION O. SUBJECTIVE WELFARE AND FOOD SECURITY

ENUMERATOR: ASK THE WOMAN OR THE MOST KNOWLEDGEABLE MEMBER IN THE HOUSEHOLD

In the past 7 days, did you worry that your household would not have enough food? 1 YES 2 NO	In the past 7 days, how many days have you or someone in your household had to: IF NO DAYS, RECORD ZERO. Rely on less preferred foods? DAYS	Limit the variety of foods eaten? DAYS	Limit portion size at meal-times? DAYS	Reduce number of meals eaten in a day? DAYS	Restrict consumption by adults for small children to eat? DAYS	Borrow food, or rely on help from a friend or relative? DAYS	Have no food of any kind in your household? DAYS	Go a whole day and night without eating anything? DAYS	harvest and collect wild foods (e.g., vegetables, birds) DAYS	How many meals, including breakfast are taken per day… ..in the household? NUMBER	…among children (6-59 months)? [WRITE DASH (-) IF NO CHILDREN 6-59] NUMBER	What did your children below 5 years old (0-4 years) have for breakfast yesterday? [USE CODES BELOW. WRITE DASH (-) IF NO CHILDREN UNDER AGE 5]	What did your children between 5 to 13 years old have for breakfast yesterday? [USE CODES BELOW. WRITE DASH (-) IF NO CHILDREN 5-13]
O1	O2a	O2b	O2c	O2d	O2e	O2f	O2g	O2h	O2i	O3a	O3b	O4	O5

Do all household members eat roughly the same diet? 1 YES ►O8 2 NO	Who and how many in the household usually eat a more diverse variety of foods, a less diverse variety of foods, (including food consumed outside the house)? 1 MORE DIVERSE 2 LESS DIVERSE Men	Women	Children (6-59 months)	In the last 12 months, have you been faced with a situation when you did not have enough quantity of food to feed the household? 1 YES 2 NO ► NEXT MODULE
O6	O7a	O7b	O7c	O8

Did you experience shortage of food in [MONTH], [YEAR]?

1 YES
2 NO

2013	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
	O9a	O9b	O9c	O9d	O9e	O9f	O9g	O9h	O9i	O9j	O9k	O9l

2014	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
	O10a	O10b	O10c	O10d	O10e	O10f						

What was the cause of this situation?

[LIST UP TO 3 IN OR DER OF IMPORTANCE]
USE CODES AT THE BOTTOM

1ST	2ND	3RD
O11a	O11b	O11c

CODES FOR O4, O5

1

TEA/DRINK WITH SUGAR
2 MILK/MILK TEA WITH SUGAR
3 SOLID FOOD ONLY (CASSAVA, SWEET POTATO, BANANA, RICE)
4 TEA/DRINK WITH SOLID FOOD (AS IN RESPONSE OPTION 3)
5 PORRIDGE WITH GROUNDNUT FLOUR
6 PORRIDGE WITH SOLID FOOD (AS IN RESPONSE OPTION 3)
7 PORRIDGE WITH SUGAR
8 PORRIDGE WITH MILK
9 PORRIDGE WITHOUT SUGAR
10 BREASTMILK
11 LEFTOVER/ T.Z (TUOZAAFI)
12 NOTHING

CODES FOR O11A, O11B, & O11C

1 INADEQUATE HOUSEHOLD STOCKS DUE TO DROUGHT/POOR RAINS
2 INADEQUATE HOUSEHOLD FOOD STOCKS DUE TO CROP PEST DAMAGE
3 INADEQUATE HOUSEHOLD FOOD STOCKS DUE TO SMALL LAND SIZE
4 INADEQUATE HOUSEHOLD FOOD STOCKS DUE TO LACK OF FARM INPUTS
5 FOOD IN THE MARKET WAS VERY EXPENSIVE
6 NOT ABLE TO REACH THE MARKET DUE TO HIGH TRANSPORTATION COSTS
7 NO FOOD IN THE MARKET
8 FLOODS/WATER LOGGING/HAILSTORM
9 NO MONEY
10 THEFT
11 FIRE
12 OTHER

SECTION P: FOOD CONSUMPTION OVER THE PAST WEEK

ENUMERATOR: ASK THE HOUSEHOLD HEAD AND THE SPOUSE (TOGETHER AND AS APPROPRIATE). FIRST ASK ABOUT ITEMS CONSUMED BY THE HOUSEHOLD (QUESTION P1) AND THEN COMPLETE P3a TO P7b. IF FOOD IS CONSUMED OUTSIDE THE HOUSEHOLD BUT NOT PURCHASED, ASK MARKET VALUE.

ITEM CODE	During the past 7 days, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram 2 Gram 3 Liter 4 Unit or Piece 5 Cane/Basket 6 Bucket 13 Headload 14 Bunch 15 Bale 16 Sachet/tube 17 Plate 18 Cup 19 Heap 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ►P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ►P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE	QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
Cereals and Cereal products											
0101	White maize										
0102	Yellow maize										
0103	Sorghum/guinea corn										
0104	Early millet										
0105	Late millet										
0106	Rice										
0107	Other grains										
0108	Buns, cakes and biscuits										
0109	Macaroni, spaghetti										
0199	Other cereal products										

ITEM CODE	During the **past 7 days**, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD. ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram, 2 Gram, 3 Liter, 4 Unit or Piece, 5 Cane/Basket, 6 Bucket, 13 Headload, 14 Bunch, 15 Bale, 16 Sachet/tube, 17 Plate, 18 Cup, 19 Heap, 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ►P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ►P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD. IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE	QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
Starches											
0201	Cassava fresh										
0202	Cassava dry/flour										
0203	Sweet potatoes										
0204	Frafra potatoes										
0205	Yams										
0206	Cocoyams										
0207	Plantains										
0299	Other starches										
Sugar and Sweets											
0301	Sugar										
0302	Sugarcane										
0303	Sweets										
0304	Honey, syrups, jams, marmalade, jellies, canned fruits										
0399	Other sweets										

ITEM CODE	During the **past 7 days**, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram 2 Gram 3 Liter 4 Unit or Piece 5 Cane/Basket 6 Bucket 13 Headload 14 Bunch 15 Bale 16 Sachet/tube 17 Plate 18 Cup 19 Heap 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ►P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ►P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE	QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
Pulses											
0401	Peas, beans, lentils										
0402	Cow peas										
0499	Other pulses										
Nuts and Seeds											
0501	Groundnuts in shell/shelled										
0502	Bambara nuts										
0503	Seeds and products from nuts/seeds (*excl.* cooking oil)										
0504	Wild nuts and seeds										
0599	Other nuts and seeds										
Vegetables											
0601	Onions										
0602	Spinach										
0603	Cabbage										
0604	Moringa										
0605	Canned, dried and wild vegetables										

ITEM CODE	During the past 7 days, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram 2 Gram 3 Liter 4 Unit or Piece 5 Cane/Basket 6 Bucket 13 Headload 14 Bunch 15 Bale 16 Sachet/tube 17 Plate 18 Cup 19 Heap 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ► P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ► P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE	QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
0606	Tomatoes										
0607	Carrots										
0608	Green pepper										
0610	Wild vegetables										
0699	Other vegetables										
Fruits											
0701	Ripe bananas										
0702	Citrus fruits (oranges, lemon, tangerines, etc.)										
0703	Mangoes										
0704	Avocadoes										
0705	Wild fruits										
0799	Other fruits										

ITEM CODE	During the **past 7 days**, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram 2 Gram 3 Liter 4 Unit or Piece 5 Cane/Basket 6 Bucket 13 Headload 14 Bunch 15 Bale 16 Sachet/tube 17 Plate 18 Cup 19 Heap 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ►P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ►P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE									
			QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
Meat, meat products, fish											
0801	Goat meat										
0802	Beef including minced sausage										
0803	Pork including sausages and bacon										
0804	Chicken and other poultry										
0805	Wild birds, insects, mice										
0806	Other domestic meat products										
0807	Bushmeat										
0808	Eggs										
0809	Fresh fish and other seafood										
0810	Smoked fish										
0811	Dried/salted fish										
0812	Package/Canned fish										
0899	Other meat										
Milk and milk products											
0901	Fresh milk										
0902	Milk products										

ITEM CODE	During the past 7 days, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram 2 Gram 3 Liter 4 Unit or Piece 5 Cane/Basket 6 Bucket 13 Headload 14 Bunch 15 Bale 16 Sachet/tube 17 Plate 18 Cup 19 Heap 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ►P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ►P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE	QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
0903	Canned milk/milk powder										
0999	Other dairy products										
Oil and fats											
1001	Cooking oil										
1002	Butter, margarine, ghee										
1099	Other fat products										
Spices and other foods											
1101	Salt										
1102	Saltpetre (kawa)										
1103	Pepper										
1104	Ginger										
1105	Ethiopian pepper										
1106	Dawadawa										
1199	Other spices										

ITEM CODE	During the past 7 days, did members of this household consume [FOOD ITEM]? PLEASE LIST NOT ONLY ITEMS CONSUMED WITHIN THE HOUSEHOLD BUT ALSO FOOD CONSUMED OUTSIDE THE HOUSEHOLD. ASK THIS QUESTION FOR ALL ITEMS, BEFORE MOVING ON TO THE NEXT QUESTIONS FOR ITEMS WITH YES		How much [ITEM] in total did your household consume in the past 7 days? 1 Kilogram 2 Gram 3 Liter 4 Unit or Piece 5 Cane/Basket 6 Bucket 13 Headload 14 Bunch 15 Bale 16 Sachet/tube 17 Plate 18 Cup 19 Heap 20 Bowl		How much [ITEM] came from purchases? IF NONE, WRITE 0 FOR QUANTITY AND ►P6a		How much did your household spend to purchase [ITEM] in total? THIS QUESTION REFERS TO THE QUANTITY REPORTED IN QUESTION P4a	How much [ITEM] came from own-production? IF NONE, WRITE 0 FOR QUANTITY and ►P7a		How much [ITEM] came from gifts and other sources? EXCLUDE FOOD TAKEN OUTSIDE THE HOUSEHOLD. IF NONE, WRITE 0 FOR QUANTITY AND WRITE DASH (-) IN P7b	
	Food item	1 YES 2 NO ►NEXT LINE	QUANTITY	UNIT	QUANTITY	UNIT	GHC total	QUANTITY	UNIT	QUANTITY	UNIT
ID	P1	P2	P3a	P3b	P4a	P4b	P5	P6a	P6b	P7a	P7b
Beverages											
1201	Tea dry										
1202	Coffee and cocoa										
1203	Other raw materials for drinks										
1204	Bottled/canned soft drinks (soda, juice, water)										
1205	Prepared tea, coffee										
1206	Bottled beer										
1207	Local brews (pito, sobolo, zomkom)										
1208	Wine and spirits										
1299	Other										
Food outside the household											
1301	Full meals (breakfast, lunch or dinner)										
1302	Barbecued meat, chips, roast bananas										
1303	Samosa, cake and other snacks										

SECTION Q1: NON-FOOD EXPENDITURES – PAST ONE WEEK & ONE MONTH

ENUMERATOR: ASK THE HOUSEHOLD HEAD AND THE SPOUSE (TOGETHER AND AS APPROPRIATE).

ONE WEEK RECALL

Item code	Over the past 7 days, did you purchase any [ITEM]?	1 YES 2 NO ►NEXT LINE	How much did you pay/purchase in total for [ITEM]? GHC
ID	Q1_1	Q1_2	Q1_3
101	Cigarettes or tobacco		
102	Matches		
103	Public transport		
104	Cell phone voucher		

ONE MONTH RECALL

Item code	Over the past 30 days, did you purchase or pay for any [ITEM]?	1 YES 2 NO ►NEXT ITEM	How much did you pay in total? GHC
ID	Q1_1	Q1_4	Q1_5
201	Kerosene		
202	Electricity, including electricity vouchers		
203	Gas (for lighting/cooking)		
204	Water		
205	Petrol or diesel		
206	Other utilities (i.e., sewage)		

ONE MONTH RECALL

Item code	Over the past 30 days, did you purchase or pay for any [ITEM]?	1 YES 2 NO ►NEXT LINE	How much did you pay in total for [ITEM]? GHC
ID	Q1_1	Q1_4	Q1_5
207	Charcoal		
208	Firewood		
209	Milling fees, grain		
210	Bar soap (for body or cloths)		
211	Clothes soap (powder)		
212	Toothpaste, toothbrush, chewing stick		
213	Toilet paper		
214	Glycerine, Vaseline, skin creams		
215	Personal care products for women (shampoo, cosmetics, hair products, etc.)		
216	Personal care products for men (shampoo, razor blades, hair products, etc.)		
217	Household cleaning products (dish soap, toilet cleansers, etc.)		
218	Light bulbs/candles/tourch batteries		
219	Phone, internet, postage stamps or other postal fees		
220	Donation - to church, mosque, charity, beggar, etc.		
221	Motor vehicle service, repair, or parts		
222	Fuel for motor cycle		
223	Bicycle service, repair, or parts		
224	Wages paid to servants		
225	Repair cost to farm implements		
226	Mortgage (regular payment to purchase house) or rent		
227	Repairs to household and personal items (radios, watches, etc.)		
228	Lotteries and raffles		
229	Sacrifice (animals)		

SECTION Q2: NON-FOOD EXPENDITURES – PAST TWELVE MONTHS
ENUMERATOR: ASK THE HOUSEHOLD HEAD AND THE SPOUSE (TOGETHER AND AS APPROPRIATE).

ITEM CODE	Over the past 12 months, did you purchase or pay for any [ITEM]? ITEM NAME	1 YES 2 NO ►NEXT ITEM	What was the cost of [ITEM] that you purchased? GHC
ID	Q2_1	Q2_2	Q2_3
301	Carpet, rugs, drapes, curtains		
302	Linen - towels, sheets, blankets		
303	Mat - sleeping or for drying maize flour		
304	Mosquito net		
305	Mattress		
306	Farm implements (e.g., cutlass, hoe)		
307	Building items - cement, bricks, timber, iron sheets, tools, etc.		
308	Health insurance fee (NHIS, etc.)		
309	Losses to theft (value of items or cash lost)		
310	Fines or legal fees		
311	Bride price /Marriage costs		
312	Funeral costs		
313	Repairs to consumer durables (e.g., repair cost for TV, Radio)		
314	Taxes for income, property, etc.		
315	Construction, repairs & maintenance to dwelling (human) (e.g., roofing sheet)		
316	Construction, repairs & maintenance to housing for animals		
317	Garments for men		
318	Garments for women		
319	Garments for children and babies		
320	Footwear for men		
321	Footwear for women		
322	Footwear for children and babies		
323	Membership fees (e.g., christian mothers association, funeral associations)		
324	School fees		
325	Motor bike		
326	Cooking utensils /jerry cans		
327	Medical expense (excluding health insurance fee)		
328	Other costs not stated elsewhere		

ITEM CODE	Over the past 12 months did you gather, purchase, or pay for any [ITEM]? ITEM NAME	1 YES 2 NO ►NEXT ITEM	What was the cost of [ITEM] that you purchased? WRITE 0 IF NOT PURCHASED] GHC	What was the estimated total value of [ITEM], from what you have gathered? [WRITE 0 IF NO GATHERING] GHC
ID	Q2_1	Q2_2	Q2_3	Q2_4
401	Wood poles, bamboo			
402	Grass for thatching roof or other use			
403	Mud bricks			

SECTION R: RECENT SHOCKS TO HOUSEHOLD WELFARE

ENUMERATOR: ASK THE HOUSEHOLD HEAD OR THE MOST KNOWLEDGEABLE HOUSEHOLD MEMBER

SHOCK ID	Over the **past five years**, was your household severely affected negatively by any of the following events? **IF THE HOUSEHOLD DID NOT EXPERIENCE ANY OF THE FOLLOWING SHOCKS, GO TO 'END THE INTERVIEW' MODULE**	1 YES 2 NO ►NEXT ITEM	Can you rank the [SHOCK] among the three most significant shocks you experienced? 1 MOST SEVERE 2 SECOND MOST SEVERE 3 THIRD MOST SEVERE **PUT CODE OF 3 BIGGEST SHOCKS**		Did [SHOCK] cause a reduction in household income and/or assets? 1 INCOME LOSS 2 ASSET LOSS 3 LOSS OF BOTH 4 NEITHER	How dispersed was this shock? It affected... 1 ONLY THIS HOUSEHOLD 2 SOME OTHER HOUSEHOLDS 3 MOST HOUSEHOLDS IN THIS COMMUNITY 4 ALL HOUSEHOLDS IN THIS COMMUNITY 5 DO NOT KNOW	In which year and month did this [SHOCK] occur/start? [ENTER -99 IF DO NOT		**How long** did the last episode of [SHOCK] last? 1 Months 2 Weeks 3 Days		What did your household do in response to this [SHOCK] to try to regain your former welfare level? **USE CODES ON RIGHT** **LIST UP TO 3 IN ORDER OF MOST RECENT INCIDENT**		
							YEAR	MONTH	DURATION	UNIT	1ST	2ND	3RD
ID	R1	R2	R3		R4	R5	R6a	R6b	R7a	R7b	R8a	R8b	R8c
101	Drought or floods			**QUESTIONS TO THE RIGHT SHOULD ONLY BE ASKED FOR THE THREE MOST SEVERE SHOCKS, AS NOTED IN QUESTION R3.** **LEAVE ALL OTHER ROWS BLANK.**									
102	Strong winds/storms												
103	Crop disease or pests												
104	Livestock died or stolen												
105	Household business failure, non-agricultural												
106	Loss of salaried employment or non-payment of salary												
107	Large fall in sale prices for crops												
108	Large rise in price of food												
109	Large rise in agricultural input prices												
110	Severe water shortage												
111	Loss of land												
112	Chronic/severe illness or accident of household member												
113	Death of a member of household												
114	Death of other family member												
115	Break-up of the household (e.g.,divorce, separation)												
116	Jailed												
117	Fire												
118	Hijacking/robbery/burglary/assault												
119	Dwelling damaged, destroyed												
120	Immediate needs of money and selling crop at lowest price												
121	Political, tribal, and farmers' livestock conflict												
122	Other												

1 RELIED ON OWN-SAVINGS

2 RECEIVED UNCONDITIONAL HELP FROM RELATIVES/FRIENDS

3 RECEIVED UNCONDITIONAL HELP FROM GOVERNMENT

4 RECEIVED UNCONDITIONAL HELP FROM NGO/RELIGIOUS INSTITUTION

5 CHANGED EATING PATTERNS (RELIED ON LESS PREFERRED FOOD OPTIONS, REDUCED THE PROPORTION OR NUMBER OF MEALS PER DAY, OR HOUSEHOLD MEMBERS SKIPPED DAYS OF EATING, ETC.)

6 EMPLOYED HOUSEHOLD MEMBERS TOOK ON MORE EMPLOYMENT

7 ADULT HOUSEHOLD MEMBERS WHO WERE PREVIOUSLY NOT WORKING HAD TO FIND WORK

8 HOUSEHOLD MEMBERS MIGRATED

9 REDUCED EXPENDITURES ON HEALTH AND/OR EDUCATION

10 OBTAINED CREDIT

11 SOLD AGRICULTURAL ASSETS

12 SOLD DURABLE ASSETS

13 SOLD LAND/BUILDING

14 SOLD CROP STOCK

15 SOLD LIVESTOCK

16 INTENSIFY FISHING

17 SENT CHILDREN TO LIVE ELSEWHERP

18 ENGAGED IN SPIRITUAL EFFORTS - PRAYER, SACRIFICES, DIVINER CONSULTATIONS

19 SMOKING AND DRINKING

20 BEGGING

21 DID NOT DO ANYTHING

22 OTHER

	END TIME	
A10d	:	
	HOUR	MIN

Thank you very much for participating in this survey and for your time!

A23 BRIEF DESCRIPTION OF LOCATION OF HOUSEHOLD - INCLUDE ANY IDENTIFYING CHARACTERISTICS OF DWELLING, NAME OF NEIGHBOURING HOUSEHOLDS & KEY PERMANENT CONTACTS, PHONE NUMBER (IF ANY).

PLEASE GIVE THE INCENTIVE TO THE HOUSEHOLD HEAD