You are Approved… So What?

Impact of Index-Insured Loans on Technology Adoption in Northern Ghana

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1. Introduction

Improving agricultural productivity is essential for reducing poverty in low-income agrarian economies in Sub-Saharan Africa (SSA). Across the region of SSA, the agricultural sector accounts for over half of total employment and one-fifth of gross domestic product (GDP) (International Monetary Fund, 2012). Agricultural productivity in this region remains low largely due to low rates of adoption and retention of improved production technologies such as fertilizers and hybrid seeds (Doss, 2006; Feder, Just, & Zilberman, 1985; Sunding & Zilberman, 2001; Tripp & Rohrbach, 2001). By improving agricultural productivity, adoption of these technologies are critical for reducing rural poverty and improving household well-being in these economies (Bourdillon et al., 2003; Kassie, Shiferaw, & Muricho, 2011; Kijima, Otsuka, & Sserunkuuma, 2008; Mendola, 2007). However, SSA countries have among the lowest rates of technology adoption in the world (Tripp & Rohrbach, 2001). The low rates of adoption are due to numerous barriers to adoption common across many developing countries. These barriers include low levels of education, poor soil quality, agro-climatic conditions, manure use, hiring of labor and extension services, cost and availability of seeds, credit constraints, informational barriers, and lack of effective commitment devices (Conley & Udry, 2010; Duflo, Kremer, & Robinson, 2008; Foster & Rosenzweig, 1995; Makokha, Kimani, Mwangi, Verkuijl, & Musembi, 2001; Ouma et al., 2002; Schultz, 1963).

Two interrelated factors are central barriers to advanced technology adoption: the riskiness of agricultural returns, primarily due to systemic weather shocks, and poor access to credit (Farrin and Miranda 2015). Agricultural production risks limit adoption by disincentivizing costly investments in new technologies. Furthermore, risk discourages banks from lending to smallholder farmers which results in poor access to credit. This poor access to credit limit farmer's ability to finance expensive and lumpy investments in agricultural inputs. Therefore, tools that help farmers to manage systemic risks should spur higher technology adoption among farmers (Carter, Cheng, & Sarris, 2011; Farrin & Miranda, 2015a; Gallenstein, Flatnes, Dougherty, Sam, & Mishra, 2017).

Index-based drought insurance (IBDI) is one tool that offers the potential to manage systemic risks to smallholder agricultural production and therefore offers considerable promise for promoting technology adoption. Index based insurance makes payouts based on objective indexes, such as measures of rainfall from rainfall stations or satellite data. By relying on these objective measures, index based insurance avoids costly asymmetric information problems and high transaction costs (e.g., the cost of assessing and validating losses) that plague conventional insurance. Hence, a carefully designed IBDI has the potential to increase credit access, repayment rates, bank profits, and technology adoption by providing payouts when the credit contract is subjected to its greatest stress (Farrin and Miranda 2015; Barnett, Barrett, and Skees 2008).

Despite the theoretical predictions of the attractiveness of IBDI, there have been mixed empirical evidence on take up of such due to factors such as lack of trust, liquidity constraints, lack of understanding of the product, and the imperfect correlation between the index and realized losses, i.e. basis risk (Cai et al. 2014; Cole et al. 2013; Giné and Yang 2009; Jensen, Barrett, and Mude 2014). In this regard, theoretical models have proposed an alternative type of index insurance where payouts go to risk aggregators such as micro-finance institutions, farmers' cooperatives, input suppliers (meso-level insurance) rather than to the farmers (micro-level insurance) (Carter, Cheng, and Sarris 2011; Miranda and Gonzalez-Vega 2010). Such a product can potentially reduce the risk of defaults and improve farmer’s creditworthiness, credit sustainability, and technology adoption (Farrin and Miranda 2015; Miranda and Gonzalez-Vega 2010). However, there is a lack of robust empirical evidence to support these predictions. Moreover, to the best of our knowledge, there are no empirical studies that explore the differential impacts of credit-linked micro- and meso-insurance on technology adoption. Therefore, the primary objective of our paper is to investigate the comparative impacts of coupling micro- and meso-level drought index insurance with agricultural loans (hereafter referred to as micro-insured loans and meso-insured loans, respectively) on agricultural technology adoption. Here, agricultural technology refers to four types of agricultural inputs: inorganic compound fertilizer, inorganic straight fertilizer, herbicide broad spectrum, and herbicide selective. In addition, we investigate the impact of treatments on total acres planted and maize yield.[1]

Our research methodology utilizes data from a three-year randomized control trial (RCT) in northern Ghana. Using micro- and meso-insured loans as separate treatments and the provision of conventional uninsured loans as the control, results of our individual fixed effects analysis indicate two major findings. First, for the total sample, we find that micro-insured loans increase farmers' adoption of compound fertilizer probability for the second year of treatment. There is no significant change for the straight fertilizer adoption probability except for the new applicants for the first year of treatment. Additionally, for herbicides, we find that micro-insured loans increase the likelihood of herbicide selective adoption by 9 percentage points for both first and second year of treatments for the total sample. For new applicants, micro- and meso-insured loans are significant in increasing the likelihood of adoption of herbicide broad spectrum and herbicide selective, respectively, in the second year of treatment. Second, micro-insured loans marginally increase the acres planted and primary crop yield in the first year of treatment for the total sample. There is no impact of meso-insured loans and none for new applicants. Overall, our findings suggest that index insured loan products, especially at the micro-level, can reduce demand-side barriers of technology adoption and encourage higher farming acreage and yields in areas with predominantly smallholder farmers.

[1] The total acres planted is proxied by acres planted for three most important crops in the baseline and follow-up rounds and two most important crops in the endline round. We found that the smallholders used majority of their land to farm two most important crops so we decided to only collect data on two crops in the endline. Similarly, maize yields is proxied by first more important crop since maize makes up 95% of the cultivation.

The remainder of the paper is structured as follows. Section 2 provides a brief context of the agricultural sector in Ghana and experimental design. Section 3 presents descriptive statistics of our study sample and the empirical framework. Section 4 presents the results and discussion. Section 5 concludes.

2. Ghanaian Context and Experimental Design

Agriculture is a critical sector of the Ghanaian economy, contributing 23% of the GDP and employing more than half of the workforce in 2012 (Ghana Statistical Service, 2014). However, a high proportion of smallholder farmers still use traditional rainfall dependent production systems (Ministry of Food and Agriculture, 2011). A primary reason for the low levels of adoption of improved production technologies is lack of access to credit (Nair & Fissha, 2010). To mitigate this issue, the Ghanaian government created a system of publicly owned rural and community banks (RCBs) (Nair & Fissha, 2010). The RCBs primarily operate as microfinance institutions, providing loans to local community farmers in groups. In addition to credit constraints, another major factor affecting Ghanaian agriculture is climate change (Ghana Insurers Association, 2015). The Ghana Agricultural Insurance Pool (GAIP) was established in March 2010 to provide agricultural insurance that protects stakeholders from drought related losses.

We partnered with the RCBs and GAIP to design and implement two treatments, micro-level (T1) and meso-level (T2) insured loan products as well as uninsured loans as a control (C).[2] We targeted these loan products to maize farmers as this is the primary crop for farmers in northern Ghana and one of the two products covered by GAIP at the time. For T1, farmer groups (FBOs) are the policy holders with any insurance payouts going directly to them. Conversely, for T2, the lender is the policy holder with the payouts going directly to the lender and credited towards the outstanding debt of the FBOs, fully forgiving

[2] Following Karlan et al. (2011), the insurance premium is covered in full by the project, and covers the full value of the loan, including the interest. Subsidizing the insurance premium allows us to ensure that there is no selection in participation based on the price of the insurance and hence measures the average treatment effect on the treated (ATT) of the insured loan products. This full subsidization allows us to also interpret our results as the impact of drought-based risk on credit market access.

the loan in the case of a full insurance payout. All loan application requirements and decision-making processes for insured and uninsured loans remained consistent with the traditional agricultural loans from the RCBs.

In November 2014, we collected a list of 791 FBOs from our 14 partner RCBs in the three northern regions of Ghana.[3] To ensure that the study targets FBOs of the greatest interest given our budget constraints, we applied five criteria to select our final sample which resulted in a sample of 258 FBOs, roughly representing 2500 farmers.[4] Ninety-eight of these FBOs are located in the Northern region in seven districts, 132 FBOs in Upper East in nine districts, and 28 FBOs in Upper West in six districts. Figure 1 presents the number of farmer groups per district in the northern regions.

[Insert Figure 1 here]

To ensure a representative sample of farmers from the FBOs, we randomly selected three members from each of the FBOs. Then we conducted a baseline survey of a total of 779 farmers in 2015. We stratified our data by regions and loan status where loan status indicates whether an eligible FBO has borrowed in the pre-baseline period or not. Stratification by loan status is motivated by our desire to explore the *extensive margin* effects of these new insured loan products, i.e., whether their availability incentivizes FBOs without previous access to agricultural credit to obtain advanced production technology. Finally, we randomly assigned FBOs to three roughly equal groups of treatments, T1 and T2, and control, C, as described earlier. Table 1 presents the number of FBOs within each region by treatment categories where the number of individual farmers are given in parentheses. We verified that T1, T2, and

[3] Our partner banks include: Bangmarigu, Bessfa, Bongo, Bonzali, Borimanga, Builsa, East Mamprusi, Lawra, Naara, Nandom, Sissala, Sonzele, Tizaa, and Toende.

[4] The criteria are as follows: (i) FGs that are in good standing with the bank in terms of borrowing record at the time of selection, potential groups that are qualified to receive loans, or groups that have been denied loans for reasons other than past default; (ii) FGs located in districts that belong to low rainfall areas (between 800mm to 1100mm annually) for maximum impact of insured products; (iii) FGs whose primary or secondary crop is maize for reasons discussed above; (iv) FGs with 7 to 15 members due to logistical and budget constraints (insurance premiums are fully subsidized); and finally (v) FGs that take out a loan of less than 10,000 Ghana Cedis (GH₵) so as to maintain a focus on the most low income groups (1 GH₵ = 0.293 USD as of February 2015).

C groups are not statistically different in terms of preexisting financial, agricultural, demographic, and geographical data--areas identified in the literature (results are available upon request).

[Insert Table 1 here]

At the end of the baseline survey, RCB loan officers met with FBOs, described the loan product to which they were assigned (i.e., micro-insured loans for FBOs under T1, meso-insured loans for FBOs under T2, and traditional agricultural loans without insurance for FBOs under C), and invited them to apply for that loan product. The description detailed the index insurance coverage for maize, subsidized nature of the insurance, and the insurance payout mechanisms (to the individual for T1 and banks for T2).[5] Then the FBOs were then left to their usual process of loan application, which they file based on the amount of credit required to buy agricultural technologies for planting. After the application, the loans are either approved or rejected by the RCBs following their usual appraisal criteria.

One year after the baseline survey, we conducted a follow-up survey in 2016. After the follow-up survey, we introduced a second year of treatments identical to the previous year, following the same timeline and the same FBOs categorization as earlier. Then we conducted an endline survey in 2017. For a more detailed description of the experimental design, see (Mishra et al., 2017).

3. Descriptive statistics and Empirical Model

3.1 Descriptive statistics

We present descriptive statistics of key variables for the baseline survey round (R0), follow-up round (R1), and endline round (R2) in Table 2. For the modern agricultural technology outcome variables, we use two types of inorganic fertilizers (compound and straight), two types of herbicides (broad spectrum and selective), acres used, and primary crop yield. Here, the total acres planted is proxied by

[5] The loan officers described the insured loans to T1 and T2 FBOs as a pilot program for the insured loans that would last for the project period to test the viability of such insured loan products in the future.

acres planted for three most important crops in R0 and R1 and two most important crops in R2. We found that the farmers used majority of their land to farm two crops with a very few of them farming a third crop so we decided to only collect data on two most important crops in the endline. Furthermore, maize yields is proxied by first most important crop since maize makes up 95% of the first most important crop. Millet makes up 30% of the second most important crop and groundnut makes up 14% of the third most important crop. In Table 2, we find that 86% of the farmers use compound inorganic fertilizer in R0, followed by 90% in R1 and 89% in R2. For straight inorganic fertilizer, they are 73, 69, and 78%, in R0, R1, and R2, respectively. For herbicide, we find that 44, 41, and 52% farmers use type broad spectrum and 19, 23, and 26% use type selective in R0, R1, and R2, respectively. Finally, only about 15% of the farmers use hybrid seeds. For traditional agricultural practices, we find that about 52% of the farmers use organic fertilizer and 86% of the farmers use traditional seeds. For acres farmed and yield outcome variables, we find that farmers use over 6 acres of their land and produce 370 kilograms of maize on average.

[Insert Table 2 here]

Among the proxies for financial access, we gathered information on whether households have savings with the bank and outstanding debt. Information on outstanding debt status is provided by the RCBs. Among those that took loans, 20 and 32% of the households have outstanding debt in R0 and R1, respectively. We also collected data on number of cattle owned and remittances as proxies for household assets and wealth. Additionally, number of good seasons out of the past five seasons served as a proxy for risk perception and number of individuals available to help at the time of drought served as a proxy for informal risk management. Lastly, household characteristics such as number of household members and age of the respondent were also collected.

We further conducted mean t-test comparisons of outcome variables by treatments for each round. Table 3 presents the t-test comparisons of input types for the all samples (Panel A) and new applicants (Panel B). We define 'new' applicants as those applicants who do not have agricultural loans from the RCBs in the pre-baseline period (i.e., loan amount of zero in pre-R0); they make up a total of 27% of the sample. From Panel A, we find that the means of compound fertilizer use for T1 are significantly higher than the C for R2. Similarly, the means of broad spectrum herbicide use for T1 are significantly higher than the C for R1. From Panel B, we find that for new applicants, the means of compound fertilizer use for T1 are significantly higher than the C for R2.

[Insert Table 3 here]

Table 4 presents mean t-test comparisons of total acres used in farming (Panel A) and maize yields (Panel B). We do not find any significant differences across treatments for either of these outcomes in Panels A or B with an exception of marginal difference in yields for T2 in R0.

[Insert Table 4 here]

3.2 Empirical Model

We use the following fixed effects (FE) model for our empirical analysis:

$$Y_{it} = \alpha + \beta \boldsymbol{T1}_{it} + \theta \boldsymbol{T2}_{it} + \lambda \boldsymbol{R}_t + \delta \boldsymbol{X}_{it} + v_i + \varepsilon_{it} \quad (12)$$

where *i* and *t* index individual and survey round, respectively. Y_{it} is a binary variable indicating the use of each of the agricultural inputs in our analysis. Alternatively, Y_{it} is a continuous variable in the total acres used for farming and maize yield estimation models. $\boldsymbol{T1}$ and $\boldsymbol{T2}$ are vectors of binary variables indicating farmers that were invited to apply for micro-insured loans (T1) and meso-insured loans (T2), respectively, in the two treatment rounds. $\boldsymbol{R}_t$ is a vector of dummy variables indicating the baseline survey (R0), the follow-up survey (R1), and the endline survey (R2). v_i is the individual level fixed effect. The parameters of interest are β and $\boldsymbol{\theta}$ which measure the impacts of T1 and T2 on outcome variables: input use, acres planted, and yields. X_{it} is a vector of respondent characteristics that may impact the outcome variable. Since our data is generated from an RCT, the inclusion of X_{it} primarily serves the purpose of improving the efficiency of the FE estimates. The control variables include whether the respondent has savings with the RCB, remittances, and bank dummies. These variables have been identified as key determinants of credit access and technology adoption in existing literature (for example, in Chakravarty and Shahriar 2010; Chakravarty and Yilmazer 2009; Karlan et al. 2011; Karlan et al. 2014). Including the bank dummies is important to control for bank-level heterogeneity as the banks are established primarily to serve a community with a specific language and culture. Lastly, since we collected data on loan status pre-study, we use our empirical model to estimate treatment effects for the new applicants.

4. Results and Discussion

To investigate the impact of our two treatments on input use, we estimate several variants of our FE model, which we group in four steps. In the first step, we estimate the treatment impacts on inorganic fertilizer use by each type (Table 5). We employ three model specifications: model one is a basic version with only the treatment and round variables; in model two, we add interaction terms between rounds and RCB dummies to control for bank-level trends over time and we add the covariates, X_{it}, discussed above; and in model three, we use the most robust specifications, model two, to estimate the treatment impacts for new applicants. In the second step, we estimate the treatment impacts on herbicide use by each type by following the first step (Table 6). In the third step, we combine the two fertilizer types into one fertilizer use binary variable and the two herbicides into one binary herbicide use variable. Then we follow model two to estimate the treatment impacts on these variables. In the fourth and final step, we estimate the treatment impacts on acres planted and yield by following the first step (Table 7). All the estimations are clustered at the FBO level.

4.1 Treatment Impacts on Input Use

Table 5 presents FE estimates of the treatment impacts on the two types of inorganic fertilizers for all and new applicants. For compound fertilizer, we find that T1 significantly increases the likelihood of compound fertilizer use by 8.7 percentage points in R2. This is significant at the 5% level. However, there is no significant impact in R1. Likewise, there is no significant impact of T2 on compound fertilizer use in either of the survey rounds. Furthermore, there are no significant impacts for new applicants. For the straight fertilizer, we find that T1 increases the likelihood of usage by 20 percentage points for new applicants in R1, however, it is only marginally significant at the 10% level. Furthermore, there are no statistically significant impacts on straight fertilizer for any of the treatments in any survey rounds for the full sample.

[Insert Table 5 here]

Table 6 presents FE estimates of the treatment impacts on the two types of herbicides for all and new applicants. For broad spectrum herbicide, we find that T1 does not have any significant impact on use in either R1 or R2. In contrast, T2 increases the likelihood of broad spectrum use by 16 percentage points for new applicants in R2. For the selective herbicide, we find that T1 increases the likelihood of usage by 8 and 9 percentage points in R1 and R2, respectively. In addition, T1 increases the likelihood of selective herbicide use for new applicants by 12.5 percentage points, however, it is only marginally significant at the 10% level. In contrast, there are no statistically significant impacts of T2 in any survey rounds.

[Insert Table 6 here]

To investigate further into the fertilizer and herbicide use, we combine both fertilizer use into one binary variable that takes the value one if farmers use both compound and straight fertilizers, and zero otherwise. Likewise, we combine both herbicide use into one binary variable which takes the value one if farmers use either of the broad spectrum or selective herbicide, and zero otherwise.[6] The FE model results are presented in Table 7. For inorganic fertilizers, we find that T1 increases the likelihood of use by 17 percentage points for new applicants in R2. For herbicide, we find that T1 increases the likelihood of usage by 9.5 percentage points in R2. In contrast, T2 has no significant impacts for either R1 or R2.

[Insert Table 7 here]

[6] Ideally, we would have wanted to create the binary value with one for those farmers who use both the herbicides, but this only makes about 15% of the sample so we opted to create the variable with value one for those farmers who use either of the two herbicides

The mostly insignificant results in the follow-up round could be due to the fact that farmers may take time to adjust their input decisions making it difficult to detect the effects in the first year of treatment. Furthermore, across the board we find insignificant results for meso-insured loans as opposed to micro-insured loans. This indicates that micro-insurance is more effective at eliciting farmer behavioral changes than meso-insurance, perhaps owing to lack of trust in the banks (Cai et al., 2014). Knowing that they will directly get the cash in case of a drought maybe be a bigger enticing factor than when the money goes to the bank first. Furthermore, farmers may be more concerned with smoothing consumption in response to drought than repaying the bank loan. If this is the case, farmers may be more responsive to micro-insurance than to meso-insurance in terms of risky input decisions. As for the extensive margin, we find that in general, treatment impacts are positively and marginally significant for agricultural technology adoption for new applicants. Lastly, both remittances and savings variables generally have expected signs, but are mostly statistically insignificant. Savings and remittances are found to be positively correlated with agricultural technology adoption in the literature (Diiro & Sam, 2015).

4.2 Treatment Impacts on Acres Used and Yield

Table 8 presents FE estimates of the treatment impacts on total acres planted and maize yields. As mentioned earlier, total acres planted is measured by total acres planted for three most important crops in R1 and two most important crops in R2. Similarly, maize yield is measured by the yield from the most important crop which composed of mostly maize (96%). The treatment impacts on these variables are only marginally significant. For example, we find that T1 significantly increases total acres planted by 1.2 acres in R1 only. In contrast, T2 does not have any significant impact in either R1 or R2. Furthermore, there are no treatment impacts on new applicants. Next, for maize yield, while T1 does not have any significant impact, T2 increases the likelihood of yields by 59 kilograms in R1. If we assume that these results are not spurious, then they indicate that farmers experiment with additional acres of land immediately with modern agricultural technologies and they would do this with the product that they are more confident in, i.e., micro-insured loans. By this intuition, we should see increased planted acres in R2 as well, but as discussed earlier, the lack of increased impact in R2 could be due to the fact that we only accounted for acres planted for two major crops in the endline survey. However, the impact on yields should not matter by the treatment type. In fact, we do find that even meso-insured loans increase yields in R1. However, the insignificant impacts of micro-insured loans on yields is not intuitively obvious. One potential reason for this difference could be due to the fact that farmers were more likely to have their agricultural loans approved by the bank in R1 if they had meso-insured loans; a result that can be seen in our companion paper (Mishra et al, 2017).

[Insert Table 8 here]

5. Conclusion and Policy Implications

Sub-saharan Africa (SSA) may face sixty percent increase in food demand over the next fifteen years (World Bank, 2016). This projection is especially concerning since this region has experienced decreasing agricultural outputs over the last decade (Suri, 2011) and Ghana is no exception (Ministry of Food and Agriculture, 2011). The lack in agricultural efficiency has been attributed to low adoption of modern agricultural technologies pertaining to barriers such as systemic production risk. In this regard, we utilize data from an RCT of drought index insured loans with two distinct treatments: farmers are offered with (i) agricultural loans coupled with index insurance, with the contract assigned to the farmer groups (Treatment 1); (ii) loans offered with insurance, but with the contract assigned to the banks (Treatment 2); and (iii) offered conventional agricultural loans without index insurance (Control).

Using a fixed effects linear probability model, we find that micro-insured loans increase the likelihood of adoption of inorganic compound fertilizer and selective herbicide by 9 percentage points in the second year of treatment. There is a marginally significant impact on technology adoption for new applicants and generally no impact in the first year of treatment. We find no impact of meso-insured loans on new technology adoption. These results confirm previous results from northern Ghana that demonstrate that risk is the central barrier to technology adoption and that micro-level index insurance can improve technology adoption (Karlan et al. 2014). However, the difference between micro- and meso-insured loans is particularly interesting. A significant behavioral response to micro-insured loans but not meso-insured loans seems to suggest that the risk of drought-induced consumption shocks, rather than drought-induced default, is a key barrier to technology adoption. This could also reflect a lack of trust in the bank to forgive their loans in the meso-insured case. This finding is consistent with (Cai et al., 2014; Cole et al., 2013). Thus, we caution that the provision of insured loans themselves are not a sufficient condition for increasing technology adoption, rather, it should be introduced with complimentary services such as trust building activities between the farmers and the banks.

Therefore, holistic policies that protect farmers from systemic risk to production and build trust among the banks and farmers can potentially boost technology adoption, even crowding in new adopters, and increase associated agricultural efficiency which is desperately needed in Ghana and SSA countries.

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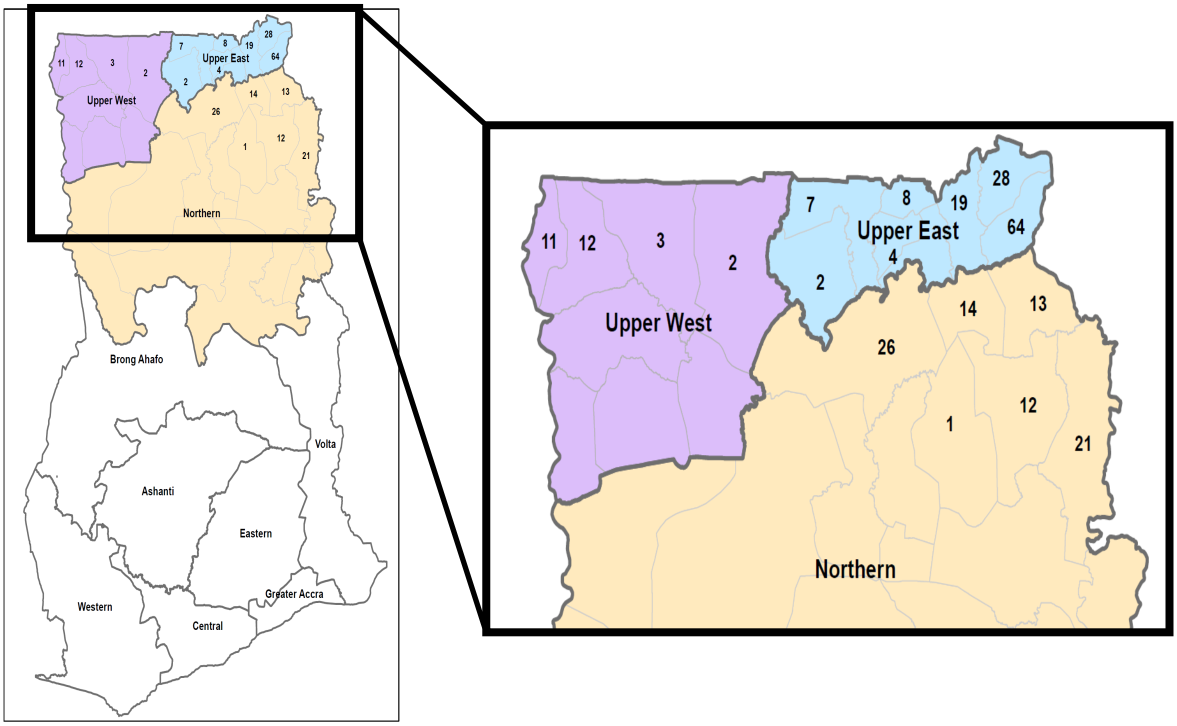
Tables and Figures

Figure 1: Map of Study Sample by District in Northern Ghana



The figure displays the number of farmer groups (FBOs) for each district represented in our sample. The 24 district names are omitted for clarity.

Table 1: Farmer groups by treatment categories and region

Treatment Status	Control	Treatment 1	Treatment 2	Total
Northern Region	33	32	33	98
	(100)	(96)	(103)	(299)
Upper East Region	44	44	44	132
	(132)	(132)	(132)	(396)
Upper West Region	9	11	8	28
	(27)	(33)	(24)	(84)
Total	87	88	87	258
	(259)	(261)	(259)	(779)

Individual farmer-level data in parentheses.

Table 2: Descriptive statistics of key variables over round

	Baseline (R0)		Follow-up (R1)		Endline (R2)	
Variables	Mean	Std.	Mean	Std.	Mean	Std.
Organic fertilizer	.445	.497	.598	.491	.505	.500
Inorg. Fertilizer compound	.862	.345	.901	.299	.894	.307
Inorg. Fertilizer straight	.728	.445	.686	.464	.782	.413
Herbicide broad spectrum	.435	.496	.413	.493	.521	.500
Herbicide selective	.186	.389	.229	.421	.259	.438
Hybrid seed	.144	.352	.165	.371	.156	.363
Traditional seed	.810	.392	.871	.335	.889	.314
Acres used for main crops	6.98	8.69	6.20	5.73	5.91	32.63
Primary crop yield (kg/acre)	363.81	316.22	359.44	314.91	385.45	388.53
Cattle	4.00	7.02	3.18	4.04	3.06	6.47
Remittances (GH₵)	100	204	124	223	97	193
Saving (1=has savings)	.68	.47	.79	.41	.71	.46
Debt (1=outstanding debt)	.20	.40	.32	.47	--	--
Respondent age	45	13	46	13	47	13
No. of HH members	8	3	10	6	9	4
Drought help	2.0	3.3	1.8	2.2	2.4	2.1
No. of last 5 good seasons	2.36	.92	2.48	.82	2.59	.88

Savings is with the bank; Draught help is the number of people the farmer can get help from in case of draught.

Table 3: Pairwise Mean Comparisons of Input Types by Survey Round

Outcome Variables	Uninsured (C)	Micro-insured	(T1)	Meso-insured	(T2)
		Panel A – Input Types for All Sample			
Compound fertilizer R0	.865	.857		.864	
Compound fertilizer R1	.903	.897		.903	
Compound fertilizer R2	.860	.939	***	.884	
Straight fertilizer R0	.745	.718		.720	
Straight fertilizer R1	.674	.693		.690	
Straight fertilizer R2	.783	.762		.802	
Herbicide Broad Spec R0	.456	.412		.437	
Herbicide Br Spec R1	.457	.360	**	.422	
Herbicide Br Spec R2	.492	.513		.558	
Herbicide Selective R0	.223	.157	*	.177	
Herbicide Selective R1	.240	.241		.205	
Herbicide Selective R2	.260	.273		.244	
		Panel B – Input Types for New Applicants			
Compound fertilizer R0	.732	.746		.750	
Compound fertilizer R1	.843	.826		.823	
Compound fertilizer R2	.771	.899	**	.765	
Straight fertilizer R0	.648	.612		.716	
Straight fertilizer R1	.643	.725		.676	
Straight fertilizer R2	.657	.681		.706	
Herbicide Broad Spec R0	.479	.484		.358	

Herbicide Br Spec R1	.429	.362		.397
Herbicide Br Spec R2	.571	.565		.632
Herbicide Selective R0	.145	.048	*	.164
Herbicide Selective R1	.186	.203		.206
Herbicide Selective R2	.257	.265		.265

*** p<0.01, ** p<0.05, * p<0.1; R0, R1, and R2 indicate baseline, follow-up, and endline rounds, respectively; new applicants are those farmers with loan status = 0 pre-baseline period.

Table 4: Pairwise Mean Comparisons of by Survey Round

Outcome Variables	Uninsured (C)	Micro-insured (T1)	Meso-insured (T2)	
Panel A – Acres Used for Farming Main Crops Outcome Variable				
All Applicants R0	7.42	6.88	6.65	
All Applicants R1	5.98	6.51	6.11	
All Applicants R2	8.30	4.96	4.50	
New Applicants R0	7.28	8.16	7.62	
New Applicants R1	6.45	7.77	7.57	
New Applicants R2	5.71	6.09	5.97	
Panel B – Primary Crop Yield Outcome Variable				
All Applicants R0	394	356	342	*
All Applicants R1	358	360	361	
All Applicants R2	390	396	370	
New Applicants R0	373	386	349	
New Applicants R1	345	365	303	
New Applicants R2	370	309	335	

*** p<0.01, ** p<0.05, * p<0.1; R0, R1, and R2 indicate baseline, follow-up, and endline rounds, respectively; new applicants are those farmers with loan status = 0 pre-baseline period.

Table 5: Linear Probability Model Treatment Impacts on Inorganic Fertilizer Adoption

	Inorganic Fertilizer Compound			Inorganic Fertilizer Straight	
VARIABLES	All Sample	All Sample	New Applicants	All Sample	New Applicants
Round 1	0.035	-0.168	-0.904***	-0.284***	0.070
	(0.026)	(0.105)	(0.131)	(0.054)	(0.131)
Round 2	-0.008	-0.231*	-1.004***	-0.275***	-0.041
	(0.029)	(0.118)	(0.106)	(0.079)	(0.133)
Treatment1 *Round1	0.004	-0.004	-0.028	0.064	0.200*
	(0.035)	(0.035)	(0.090)	(0.052)	(0.105)
Treatment1 *Round2	0.089**	0.087**	0.112	0.014	0.124
	(0.038)	(0.036)	(0.083)	(0.052)	(0.096)
Treatment2 *Round1	0.000	-0.001	-0.017	0.008	0.001
	(0.037)	(0.038)	(0.098)	(0.055)	(0.093)
Treatment2 *Round2	0.023	0.022	0.002	0.005	-0.019
	(0.038)	(0.038)	(0.087)	(0.051)	(0.098)
Saving binary (1=has savings)		0.014	0.002	0.050*	0.060
		(0.019)	(0.046)	(0.026)	(0.062)
Remittances		0.000	-0.003	0.000	0.009
		(0.000)	(0.010)	(0.000)	(0.000)
Constant	0.864***	0.854***	0.747***	0.690***	0.613***
	(0.009)	(0.016)	(0.037)	(0.021)	(0.048)
Bank dummies	No	Yes	Yes	Yes	
Observations	2,330	2,327	619	2,326	618
R-squared	0.012	0.039	0.084	0.134	0.099
Number of HHID	779	779	208	779	208

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses; R1 and R2 indicate follow-up and endline rounds, respectively; Baseline round (R0) is excluded from the dummy; Treatment 1 and Treatment 2 indicate micro- and meso-insured loans, respectively; Uninsured loan (C) has been excluded from the dummy; Thirteen rural community banks have been included in the dummy with one excluded bank.

Table 6: Linear Probability Model Treatment Impacts on Herbicide Adoption

	Herbicide Broad Spectrum			Herbicide Selective	
VARIABLES	All Sample	All Sample	New Applicants	All Sample	New Applicants
Round 1	0.004	-0.148***	-0.218	-0.012	0.037
	(0.041)	(0.051)	(0.133)	(0.053)	(0.122)
Round 2	0.039	-0.160**	-0.130	-0.001	0.044
	(0.038)	(0.075)	(0.121)	(0.075)	(0.086)
Treatment1 *Round1	-0.055	-0.067	-0.097	0.080*	0.097
	(0.058)	(0.054)	(0.102)	(0.046)	(0.081)
Treatment1 *Round2	0.063	0.067	-0.014	0.089**	0.125*
	(0.058)	(0.053)	(0.108)	(0.045)	(0.069)
Treatment2 *Round1	-0.012	-0.002	0.101	-0.001	-0.003
	(0.060)	(0.055)	(0.089)	(0.048)	(0.097)
Treatment2 *Round2	0.088	0.067	0.163*	0.013	-0.032
	(0.061)	(0.056)	(0.092)	(0.044)	(0.072)
Saving binary (1=has savings)		0.010	-0.034	-0.008	-0.013
		(0.028)	(0.064)	(0.023)	(0.045)
Remittances		-0.014**	-0.023*	0.004	0.013
		(0.007)	(0.014)	(0.005)	(0.011)
Constant	0.433***	0.442***	0.479***	0.187***	0.116***
	(0.014)	(0.023)	(0.047)	(0.019)	(0.035)
Bank dummies	No	Yes	Yes	Yes	Yes
Observations	2,322	2,319	615	2,314	610
R-squared	0.021	0.079	0.188	0.059	0.114
Number of HHID	779	779	208	779	208

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses; R1 and R2 indicate follow-up and endline rounds, respectively; Baseline round (R0) is excluded from the dummy; Treatment 1 and Treatment 2 indicate micro- and meso-insured loans, respectively; Uninsured loan (C) has been excluded from the dummy; Thirteen rural community banks have been included in the dummy with one excluded bank.

Table 7: Linear Probability Model Treatment Impacts on Higher Adoption Levels of Inputs

	Inorganic Fertilizers Both		Herbicide Either	
VARIABLES	All Sample	New Applicants	All Sample	New Applicants
Round 1	-0.443***	-0.925***	-0.177***	-0.201
	(0.133)	(0.134)	(0.060)	(0.133)
Round 2	-0.478***	-1.091***	-0.128*	-0.110
	(0.148)	(0.117)	(0.076)	(0.117)
Treatment1 *Round1	0.044	0.163	0.013	-0.036
	(0.053)	(0.110)	(0.055)	(0.113)
Treatment1 *Round2	0.056	0.173*	0.095*	0.042
	(0.051)	(0.088)	(0.052)	(0.110)
Treatment2 *Round1	-0.021	-0.040	0.033	0.103
	(0.056)	(0.101)	(0.055)	(0.094)
Treatment2 *Round2	0.032	0.033	0.045	0.121
	(0.049)	(0.090)	(0.054)	(0.092)
Saving binary (1=has savings)	0.039	0.059	0.010	-0.010
	(0.026)	(0.057)	(0.029)	(0.064)
Remittances	0.003	0.000	-0.011*	-0.015
	(0.005)	(0.012)	(0.006)	(0.014)
Constant	0.675***	0.572***	0.526***	0.494***
	(0.021)	(0.044)	(0.023)	(0.049)
Bank dummies	Yes	Yes	Yes	Yes
Observations	2,326	618	2,313	610
R-squared	0.128	0.105	0.064	0.131
Number of HHID	779	208	779	208

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses; R1 and R2 indicate follow-up and endline rounds, respectively; Baseline round (R0) is excluded from the dummy; Treatment 1 and Treatment 2 indicate micro- and meso-insured loans, respectively; Uninsured loan (C) has been excluded from the dummy; Thirteen rural community banks have been included in the dummy with one excluded bank.

Table 8: Treatment Impacts on Acres Planted and Primary Crop Yield

	Acres Planted		Primary Crop Yield	
VARIABLES	All Sample	New Applicants	All Sample	New Applicants
Round 1	-2.467**	2.513	88.861	-94.944
	(1.237)	(1.645)	(60.104)	(80.622)
Round 2	-0.407	1.382	124.400*	-102.530*
	(4.166)	(1.633)	(67.167)	(59.589)
Treatment1 *Round1	1.227*	0.200	36.274	18.450
	(0.726)	(1.233)	(31.539)	(74.204)
Treatment1 *Round2	-2.598	-0.306	44.694	-53.679
	(3.487)	(1.633)	(45.967)	(59.460)
Treatment2 *Round1	0.926	0.551	58.875*	-0.920
	(0.930)	(1.211)	(34.973)	(66.828)
Treatment2 *Round2	-3.211	-0.664	32.339	3.034
	(3.677)	(1.286)	(35.294)	(54.551)
Saving binary (1=has savings)	-0.601	0.222	25.647	4.354
	(0.995)	(0.899)	(16.813)	(41.849)
Remittances	0.113	0.175	7.015	5.544
	(0.113)	(0.118)	(5.889)	(8.519)
Constant	7.262***	7.341***	339.514***	362.819***
	(0.363)	(0.943)	(13.731)	(34.121)
Bank dummies	Yes	Yes	Yes	Yes
Observations	2,313	613	2,316	617
R-squared	0.008	0.107	0.036	0.068
Number of HHID	779	208	779	208

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses; R1 and R2 indicate follow-up and endline rounds, respectively; Baseline round (R0) is excluded from the dummy; Treatment 1 and Treatment 2 indicate micro- and meso-insured loans, respectively; Uninsured loan (C) has been excluded from the dummy; 13 community banks have been included in the dummy with one excluded bank; total acres planted includes three major crops in R1 and two major crops in R2.