Index-Insured Loans and Smallholder Access to Agricultural Credit: An Experimental Study in Northern Ghana

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Abstract

We conducted a two-treatment randomized control trial in northern Ghana to investigate how bundling index insurance with smallholder farmer agricultural production loans affects the demand and supply of credit. In one treatment, farmer groups were invited by lenders to apply for production loans bundled with an index insurance contract that, in the event of a drought, indemnifies farmers directly (micro-insurance). In the second treatment, farmer groups were invited to apply for production loans bundled with an index insurance contract that, in the event of a drought, indemnifies the lender directly on the condition that the indemnity be used to retire the farmer's debt obligation (meso-insurance). Farmers in a control group were invited to apply for uninsured loans. We find that although bundling index insurance with agricultural loans does not significantly increase loan applications submitted by farmer groups, it significantly increases the proportion of loan applications approved by lenders. We also find that approvals of loan applications by lenders are significantly greater with meso-insured loans than micro-insured loans.

Key words: index-insurance; smallholder credit access; Ghana

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1. Introduction

Investment in advanced agricultural production technologies offers a promising pathway for reducing rural poverty in the developing economies of Sub-Saharan Africa (Mendola, 2007; Kassie, Shiferaw & Muricho, 2011; Feder, Just & Ziberman, 2003). However, investment in agriculture in these countries continues to be severely impeded by lack of access to affordable credit, particularly among the tens of millions of poor smallholders who account for the majority of agricultural production. In Sub-Saharan Africa (SSA) today, agriculture employs about 55% of the population, yet accounts for only 1% of bank lending and, in any given year, less than 5% of adults in rural areas obtain loans from formal financial institutions (International Finance Corporation, 2014).

Lack of access to formal credit by poor smallholders has been attributed to a variety of interrelated and mutually reinforcing factors, including: asymmetric information problems (i.e., moral hazard and adverse selection) that derive from high costs of monitoring contract performance and paucity of public credit history information; ineffective and costly legal contract enforcement and ill-defined property rights; ineffective and distorting government policies, such as frequent ad hoc loan forgiveness mandates; high transaction costs due to the remoteness and geographic sparseness of rural dwellers; and lack of expertise among financial institutions in managing agricultural loan portfolios (Besley, 1994; Binswanger & van den Brink, 2005; Conning & Udry, 2007; Stiglitz & Weiss, 1981; Boucher, Carter & Guirkinger, 2008).

However, two salient features that distinguish smallholders from other populations stand out as the root causes of their lack of access to formal credit: the inability of poor smallholders to provide adequate collateral to securitize their loans and the high and covariant risk associated with rain-fed agricultural production. These factors, in combination, threaten lender solvency by exposing them to the risk of widespread loan defaults in the event of a drought or other natural catastrophe that affects large numbers of smallholder borrowers simultaneously. As such, lenders in SSA have generally limited their credit services to urban and peri-urban populations or well capitalized farmers and agricultural enterprises capable of presenting adequate collateral (Meyer, 2007).

In order to address the collateral and risk problems endemic to smallholder agricultural credit, researchers and policymakers have begun to explore combining two distinct financial technologies independently designed to address the two underlying problems: joint liability group credit and index insurance. Joint liability group credit is designed to address the lack of collateral among the poor. Joint liability group credit, loans are offered to groups, rather than individuals, with individual group members held jointly and severally liable for meeting the collective loan repayment obligations of the entire group. Joint liability group credit, in principle, employs peer monitoring and moral suasion as a substitute for hard collateral requirements (Stiglitz, 1990; Banerjee, Besley & Guinnane, 1994; Besley & Coate, 1995; Ghatak & Guinnane, 1999).

Index insurance is designed for managing systemic agricultural risks such as widespread droughts (Miranda, 1990; Miranda & Farrin, 2012; Barnett, Barrett & Skees, 2008). Unlike conventional insurance, index insurance indemnifies the insured based on the observed value of a specified “index”' or other closely related variable that is objectively observable and highly correlated with the losses of the insured, and which additionally cannot be influenced by the actions of the insured. The most widely used index in insurance contract designs in developing countries are rainfall measured at nearby ground meteorological stations or vegetation indices based on satellite observations. Index insurance, in principle, is free of the moral hazard and adverse selection problems that render conventional forms of insurance inviable for agriculture in developing countries, and can be delivered at much lower administrative costs, making it more suitable for insuring agricultural risk in developing countries.

Recent theoretical research suggests that bundling index insurance with agricultural loans has the potential to increase credit market access among smallholder farmers in developing countries (Marr et al, 2016; Carter, Cheng, & Sarris, 2011, 2016; Farrin & Miranda, 2015; Gine & Yang, 2009). Carter, Cheng, & Sarris (2016) analyze a static theoretical model and find that bundling index insurance with agricultural credit leads to increased investment in improved production technologies. Farrin & Miranda (2015) and Miranda & Gonzalez-Vega (2011) conduct a similar analysis in a dynamic framework. They find that bundling index insurance with smallholder agricultural loans reduces rates of default, particularly in the event of a drought or other natural catastrophe, thereby reducing the lender’s risk of insolvency, allowing them to increase the volume of loans they offer.

Recent theoretical research also suggests that the beneficiary to the insurance indemnity and restrictions on its use has important implications for the impact of index insurance on credit supply and demand. Two approaches to bundling index insurance to loans have received most attention among researchers and policymakers. “Micro-insured” loans require the borrower to acquire a personal index insurance contract to which he/she is the beneficiary. “Meso-insured” loans require the borrower to acquire an index insurance contract, but to name the lender as the beneficiary on condition that the lender use the indemnity to retire the borrower’s debt obligation.

Intuitively, micro-insured loans are more attractive to the borrower than meso-insured loans, since the former, in the event of a drought, offer the smallholder the option to use insurance payouts to finance household consumption shortfalls rather than to repay their loans. Conversely, meso-insured loans are more attractive to the lender, as they preclude the possibility of widespread defaults in the event of a drought. Farrin & Miranda (2015) and Miranda & Gonzalez-Vega (2011) predict that loan repayment rates will be higher with either micro- or meso-insured loans. However, meso-insured loans will be more effective at reducing the risk born by lenders, allowing them to increase the volume of loans they offer and to decrease the interest rates they charge on those loans. Carter, Cheng & Sarris (2016), on the other hand, predict that micro-insured loans will have no impact on bank behavior as the bank does not internalize the presence of the insurance.

In order to investigate how bundling index insurance with smallholder production loans affects the demand and supply of credit, we conducted a two-treatment randomized control trial involving 258 groups of maize farmers in northern Ghana. In one treatment, farmer groups were invited by lenders to apply for production loans bundled with an index insurance contract that, in the event of a drought, indemnifies the farmers directly (micro-insurance). In the second treatment, farmer groups were invited to apply for production loans bundled with an index insurance contract that, in the event of a drought, indemnifies the lender directly on the condition that the indemnity be used to retire the farmer's debt obligation (meso-insurance). Farmers in a control group were invited to apply for uninsured loans. We find that although bundling index insurance with agricultural loans does not significantly increase loan applications submitted by farmer groups, it significantly increases the proportion of loan applications approved by lenders. We also find that approvals of loan applications by lenders are significantly greater with meso-insured loans than micro-insured loans.

Our work contributes to the development finance literature in two ways. First, to our knowledge, we are the first to empirically investigate the comparative impacts of bundled micro- and meso-insured loans. Second, our investigation explores how bundling index insurance with loans affect both the demand for and supply of credit, whereas the extant empirical literature focuses exclusively on the demand side (Giné & Yang, 2009; Karlan, Kutsoati, McMillan, & Udry, 2011; Stein, 2016).

The remainder of the paper is organized as follows. Section 2 explains our experimental design. Section 3 describes our empirical model and estimation strategy, including the hypotheses to be tested. Section 4 presents our estimation results. Section 5 provides a summary of our findings, compares them to other recently published findings, and offer our conclusion and policy recommendations.

2. Experimental Design

Our randomized control trials (RCT) treatments were carried out during the 2015 and 2016 major growing seasons in the three northern regions of Ghana: Upper East, Upper West, and Northern. In these regions, smallholder agriculture is the dominant source of employment and farmers rely heavily on rainfed agricultural practices, with maize the dominant crop. The area faces the greatest threat of drought and lowest total rainfall in Ghana, making it a suitable location to investigate the impact of index insurance on credit market access.

2.1. Institutional Partners

We worked with two institutional partners in Ghana to develop and implement the insured agricultural loans which formed the basis for our RCT: the Association of Rural Banks (ARB) and the Ghana Agricultural Insurance Programme (GAIP).

The ARB is an organization that promotes, represents, and provides services to a network of rural and community banks (RCBs) across Ghana. The RCBs were initiated in 1976 by the Ghanaian government to promote financial market access in rural and underserved areas. The RCBs operate in specified geographic, cultural, and linguistic areas with the intention of providing financial services, including credit to rural enterprises and farmers; to date, the RCBs are the largest providers of formal financial services in rural areas, representing about half of the total banking outlets in Ghana (Steel & Andah, 2003; Owusu-Frimpong, 2008; Nair & Fissha, 2010).

We specifically worked with the ARB-Northern Ghana Chapter, which represents the 16 RCBs operating in the Northern, Upper East, and Upper West regions of Ghana. The RCBs primarily provide loans to farmers in groups, i.e., farmer-based organizations (FBOs), which are organized by farmers organically and facilitated by extension agents from the Ministry of Food and Agriculture (MOFA) or in collaboration with the government sponsored Northern Rural Growth Programme (NRGP). Through the ARB-Northern Ghana Chapter, we ultimately worked with fourteen of the sixteen RCBs in the three northern regions: Bangmarigu, Bessfa, Bongo, Bonzali, Borimanga, Builsa, East Mamprusi, Lawra, Naara, Nandom, Sissala, Sonzele, Tizaa, and Toende.

The Ghana Agricultural Insurance Program is a private insurance company initially founded in 2001 by the Ghanaian government, the German Society for International Cooperation (GIZ), and Ghanaian insurance companies to help farmers manage agricultural production risks including climate change (Ghana Insurers Association, 2015). Currently, GAIP offers a variety of indemnity and index insurance policies for maize, soy, and other leading crops and is the exclusive provider of agricultural index insurance in the country.

2.2. Treatment Arms - Insured Loan Contracts

In collaboration with GAIP and the fourteen RCBs from northern Ghana, we designed insured loan products that would serve as the basis for our experimental analysis. These insured loans combined a conventional agricultural loan from an RCB and a rainfall-based index insurance contract from GAIP.

Loan contract provisions varied across banks, but followed each bank's established credit policies and procedures Loans generally provided smallholder groups with capital to purchase agricultural inputs including plowing services, fertilizer, herbicides, certified seeds, and other inputs. Some banks offered predominantly cash loans, while others provided vouchers that could be redeemed for the necessary inputs. More specifically, five RCBs offered primarily cash loans (accounting for 92 FBOs) at baseline and nine RCBs offered primarily in-kind loans (accounting for 166 FBOs). The loans typically required borrowers to begin repaying at the time of harvest with the full repayment amount due ten months after the issuance of the loan.

We used existing GAIP index insurance contracts for maize as the index insurance component of the insured loans. The insurance contract make payouts based on objective measures of rainfall using a three-trigger mechanism (Stutley, 2010). For the index, GAIP used a combination of rainfall station measurements and satellite estimates of rainfall using United States National Oceanic and Atmospheric Administration data. The trigger schedule was designed to closely match the rainfall input needs for maize over its three major agronomic phases. The first payout, which occurs at the conclusion of the germination phase, is based on the number of consecutive dry days (a dry day is a day with less than 2.5mm of rain) or on dekad (10-day period) with an insufficient total rainfall (25mm) within the germination period of the maize crop. The second payout, which occurs at the conclusion of the crop growth phase, is based on consecutive dry days during the period between germination and flowering. The third payout, which occurs at the conclusion of the flowering phase, is based on total quantity of rain (begins paying out if rainfall is below 150mm for the flowering period) during the flowering period. The specific triggers and time periods vary by geographical location due to variations in the start and end of the growing season.

The final insured loans combine the insurance contract from GAIP and the loan contracts from the participating RCBs. The research team purchased insurance contracts covering the value of the loan (principle plus interest) issued by the RCBs and provided them to farmer groups and banks at no cost to them. We developed micro-insured loans and meso-insured loans by varying the policy holder and beneficiary of the insurance component. For micro-insured loans, insurance contracts identified the individual borrower as the beneficiary; for meso-insured loans, the bank was identified as beneficiary.

With these insured loans in place, we designed our treatment arms. Specifically, we created one control group and two treatment groups:

- Control Group (C): FBOs were invited to apply for conventional agricultural loans from their respective RCBs. These loans followed standard loan contract structures without any insurance component.
- Treatment 1 (T1): FBOs were invited to apply for micro-insured loans. That is, the loans were bundled with an index insurance policy for which the borrower was the beneficiary.
- Treatment 2 (T2): FBOs were invited to apply for meso-insured loans. That is, the loans bundled with an index insurance policy for which the bank received any payouts on condition that the payouts be credited towards the FBO's outstanding debt.

Farmers in C, T1, or T2 groups were offered the opportunity to apply for loans following established bank credit policies and procedures, but were not guaranteed that their loan would be approved. This design allowed us to observe how bundling insurance with agricultural credit affects both the demand and supply of credit market.

2.3. Sample Selection, Implementation and Timeline

We visited northern Ghana in November 2014 and obtained a sample of 791 potential and current FBO clients of the fourteen participating RCBs which constituted our sample frame. Out of these, for our final sample, we selected 258 FBOs that all of the following four criteria: (i) current FBO borrowers and qualified potential FBOs that were denied loans in the past for reasons other than past default; (ii) FBOs whose primary or secondary crop is maize as this is the most common crop and corresponded to the insurance product; (iii) FBOs with 7 to 15 members due to logistical and budget constraints; and finally (iv) FBOs that take out a loan of less than 10,000 Ghana Cedis (GH₵).[2] Our sample was distributed throughout the three northern regions as shown in Figure 1.

[Figure 1]

[2] 1 GH₵ = 0.293 USD as of February 2015.

We collected our baseline survey in February and March of 2015. We surveyed three randomly selected farmers from each FBO resulting in a sample of 779 farmer.[3] Using the baseline survey, we stratified our sample by region and by borrower status in the year prior to the baseline. We stratified on region due to significant cultural and geographic differences between regions and on borrower status to account for differences between existing and new clients. After stratification, we randomly assigned FBOs to either T1, or T2, or C categories as described earlier at the end of March 2015. Using the baseline data, we conducted balancing tests to ensure successful randomization (see Table A1 in Appendix).

The first treatment intervention was administered in the summer of 2015. GAIP aided us with training loan officers from each RCB on the design of the index insurance products and the specific insured loan contract structure. Subsequently, loan officers invited FBOs to apply for loans corresponding to their treatment assignments. After the invitations, FBOs followed their regular window of application and applied for loans in April to May 2015. Subsequently, in May to June 2015, the RCBs made loan approval decisions following their standard appraisal criteria and disbursed loans. Other than the risk protection afforded by the drought index insurance, no further benefit accrued to FBOs or banks with insured loans. The loan application and approval criteria, interest rates, payment schedules, and all other contract features for the insured loans were identical to those of conventional agricultural loans. One year after the baseline survey, we conducted a follow-up survey on 99% of the baseline sample from February to March 2016.[4] After the follow-up survey, we introduced a second round of treatments identical to the previous year following the same timeline and the same FBOs categorization as in the previous year. We then conducted an endline survey from March to April 2017. See Figure 2 for a detailed map of the RCT process.

[Figure 2]

2.4. Descriptive Statistics

Table 1 presents descriptive statistics of key variables for the baseline round (R0), follow-up round (R1), and endline round (R2). Time invariant variables are presented for R0 only. We discuss a selection of these variables in this subsection.

First, we gathered information on our key outcome variables and a variety of other financial access variables: whether they have a loan, loan application, loan approval, whether households have savings with the bank, outstanding debt, and their 2014 borrower status (whether they were active

[3] Roughly three farmers per group with five additional surveys resulting from miscommunications in the field. On three occasions, enumerator teams accidentally collected more than three surveys from a farmer group.

[4] A total of eight missing respondents were replaced by randomly selected farmers of the same gender from their respective FBOs.

borrowers at the time of sampling). Information on outstanding debt status is provided by the RCBs. We found that 70% of the sample had a loan at baseline, which declined to 63% in R1 and 36% in R2. To get the most accurate information on our primary outcome variables, loan application and approval, we matched our survey data from R0 and R1 rounds against data provided by FBO secretaries and RCBs. Doing so, we found that 91% of the sample applied for loans in R0, of which 76% were approved. The high application rate is due to the fact that the sample frame consists mostly of RCB clients who have been applying for loans for many years. For R1, 80% of the farmers applied for loans, of whom 79% were approved and for R2, 57% of the farmers applied for loans, of whom 63% were approved.[5] Among farmers that took loans, 20 and 32% have outstanding debt in R0 and R1, respectively. For savings, 68% of the sample has savings in R0, which increased to 78% in R1 and 71% in R2.

[Table 1]

Second, we collected data on agricultural production of maize as maize was our primary crop of interest and the crop for which the insurance policy was designed. We find that land cultivated with maize is 2.9, 2.7, and 2.6 acres for R0, R1, and R2 respectively. Maize yields are 326, 346, and 361 for R0, R1, and R2, respectively. These yields translate into revenue from maize cultivation of 883 GH₵, 1023 GH₵, and 917 GH₵ for R0, R1, and R2 respectively. The average loan size for farmers in our sample was 321 GH₵, 415 GH₵, and 444 GH₵ for R0, R1, and R2, respectively. Therefore, the loan size is roughly 41% of average maize revenue.

Third, we collected data on the number of agricultural plots owned, cattle ownership, and remittances as proxies for household assets and wealth. Among these, we find that the number of plots used for farming and remittances are significantly higher in R1. Third, we collected data on risk perception, willingness to take risks, and mechanisms to cope with risk. To measure willingness to take risks, we use a self-reporting technique using a five-point Likert scale ranging from very willing to take risks to not at all willing to take risks (Hardeweg, Menkhoff and Waibel, 2013). Seventy two percent of the farmers report willing or very willing to take risks.

In Table 2, we report mean t-test comparisons of having a loan, loan applications, and loan approvals for R0, R1, and R2 in Panels A, B, and C, respectively. As expected, we do not find any significant differences in means for any of the three outcome variables between T1, T2, and C

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[5] Although we do not have quantitative data to justify this trend, our qualitative discussions with the farmers indicated that the announcement of the amount of the government subsidy for fertilizers and seeds came unusually late which resulted in many FBOs missing the deadline for loan application in R1. In addition, we found that the Ghanaian government implemented an eight-year program titled the Northern Rural Growth Programme (NRGP) which sought to facilitate the borrowing process between the farmers and banks. This program ended in 2016, right before our R2 of the intervention (IFAD, 2014). Overall, roughly 62% of our sample was covered by the NRGP. This could have caused an unusually low rate of application and approval in R2. Lastly, there was an ethnic conflict and violence in the Upper East region during R2, which displaced some of the FBOs and hence might have impacted their loan application and approvals. We address these challenges later in Results section.

groups in R0; this is consistent with randomization of the treatment assignment. The means for having a loan is higher for T1 and T2 in R1 and higher for T2 in R2 (Panel A). The means of loan application are significantly higher for T1 group in R1 and R2 (Panel B). Similarly, the means of loan approval are significantly higher for both T1 and T2 groups than the C group in R1 and R2 (Panel C).

[Table 2]

3. Empirical Model

Our empirical model is designed to test three hypotheses regarding the impact of bundling index insurance with smallholder agricultural loans:

> *H1: Bundling index insurance with loans will increase smallholder demand for agricultural credit, and more so with micro-insured loans than meso-insured loans*
>
> *H2: Bundling index insurance with loans will increase lender supply of smallholder agricultural credit, and more so with meso-insured loans than micro-insured loans.*
>
> *H3: Bundling index insurance with loans will increase the number of loans secured by smallholders.*

We investigate the impact of insured loans on agricultural credit access in two steps. In Step 1, we examine the effect of insured loans on credit market access by looking at the treatment impacts on having a loan (here on referred to as *haveloan* variable). Since having a loan is composed of both the farmer's decision to apply for a loan and the bank's decision to approve the loan, we further attempt to disentangle the impacts in Step 2. Here, we investigate the impact of insured loans on credit demand by identifying the treatment effects on the loan application decision and the impact of insured loans on credit supply by identifying the treatment effects on loan approval. For these estimations, we use a series of econometric models to progressively build more efficient models and incorporate robustness checks. We describe these models below.

First, we include a model that contains the simplest difference-in-differences (DID) model based on our RCT design; the model of estimation is as follows:

$$Y_{it} = \alpha + \gamma T1_i + \ \mu T2_i + \boldsymbol{\lambda}'\boldsymbol{R_t} + \ \boldsymbol{\theta}'(\boldsymbol{T1_i} * \boldsymbol{R_t}) + \ \boldsymbol{\beta}'(\boldsymbol{T2_i} * \boldsymbol{R_t}) + \boldsymbol{\delta}'\boldsymbol{X_{it}} + \ \varepsilon_{it} \qquad (1)$$

Equation 1 includes the indicators for treatment status, $T1_i$ and $T2_i$, i.e., micro-insured loan and meso-insured loan, respectively; R_t as an indicator variable for survey round (1 = follow-up round and 2 = endline round); their interaction terms; and dummies, indicated by X_i, for whether the farmer is a recent borrower and geographic regions to comply with the randomization design (i.e., borrower status and regional-level stratification during treatment assignment). ε_{it} is an error term; *i* and *t* index individual and survey round, respectively. Y_{it} is the outcome variable; for Step 1, Y_{it} takes a value of one for farmers who have loans and zero otherwise. For Step 2, for loan application estimation, Y_{it} takes a value of one if a farmer applied for a loan and for loan approval estimation, Y_{it} takes a value of one if the farmer's loan is approved. This estimation is presented as Model 1 (Tables 3-5). The coefficients θ and β are of main interest; they capture the impacts of the two treatments on credit access.

Next, we add bank-year fixed effects (an interaction term between round dummies and the RCBs in Equation 1) and a dummy variable, outstanding debt, indicating if the borrower was behind on her loan payments at the time of our baseline survey; these results are presented as Model 2 (Tables 3-5). We control for bank-year effects as we believe that there are important factors that differ between banks and that these factors may have changed over time. As mentioned earlier, these banks operate in regions with different ethnicities and languages which can spur heterogeneity in credit access of the farmers. Moreover, some events that occurred during our experiment may have affected banks differently. For example, during our follow-up survey, we found that several districts in the Upper East region experienced ethnic violence which could have temporarily affected credit access for banks in this region. Additionally, during our second round of intervention, a government sponsored program that promoted financial inclusion in the north, the Northern Rural Growth Programme (NRGP), ended. Banks in our sample were likely to have been affected differently by the ending of the NRGP program.[6] We control for late payments at the baseline year to control for any possible differences in loan repayment probabilities that may interfere with receiving future loans. Finally, we estimate an individual-level fixed effects regression (FE) model of the treatment impacts; this estimation is presented as Model 3 (Tables 3-5) and has the following empirical specification:

$$Y_{it} = \alpha + \beta' \boldsymbol{T1_{it}} + \theta' \boldsymbol{T2_{it}} + \boldsymbol{\gamma}'\boldsymbol{R_t} + \boldsymbol{\delta}'\boldsymbol{X_{it}} + v_i + \varepsilon_{it} \tag{2}$$

where v_i is the time invariant component of the error term that will be controlled for using fixed effects estimation, while ε_{it} is the remaining individual and time variant error term. As represented earlier, $\boldsymbol{T1_{it}}$ and $\boldsymbol{T2_{it}}$ are vectors of treatment variables indicating the treatment category assignment for follow up and endline years. $\boldsymbol{X_{it}}$ now includes time-variant observables, having savings with the bank and remittances, that have been identified as key determinants of credit access and technology adoption in the literature (Chakravarty & Shahriar, 2010; Chakravarty & Yilmazer, 2009; Karlan et al., 2011; Karlan et al., 2014). Since our data is generated from an RCT, the inclusion of $\boldsymbol{X_{it}}$ primarily serves the purpose of improving the efficiency of the estimates. In practice, it makes little difference whether we include this vector or not when it comes to the treatment effects (see Models 1-3 in Tables 3-5 that report the results without and with covariates,

[6] In fact, roughly half of the bank-year dummies are significant at standard levels in Model 2 in Step 1 (results available upon request).

respectively). Standard errors are always clustered at the FBO-level for both Equations 1 and 2, which is the unit of randomization (Moulton, 1986).

In Step 2, we employ Equations 1 and 2 to estimate the treatment impacts on loan application and loan approval outcome variables. However, we note that the approval decision is observed only for farmers who apply for loans. Therefore, if the error terms from the application and approval variables are correlated, we will get biased estimates of the treatment impacts on loan approval. This correlation may arise from omission of one or more variables that determine both application and approval. We conduct a mean t-test comparison of selected variables by the two outcome variables, apply and approve (Table A2 in Appendix). Among these variables, we find that savings and remittances are significantly different across both variables so we control for these variables in our empirical models (Model 3 in Tables 3-5) for loan application and approval. We further address the potential sample selection bias by following Wooldridge (2010) and adopting a fixed effects version of the Heckman Sample Selection Model (HSSM) (Heckman, 1976, 1979). We use a two-stage estimation process. First, we estimate the selection process by using probit models for each of the survey rounds and use the estimates to generate round-specific inverse mills ratios. The first stage probit models follow equation 3,

$$A_i = I(\alpha + \beta T1_i + \theta\, T2_i + \boldsymbol{\sigma}'\boldsymbol{X_i} + \boldsymbol{\vartheta}'\boldsymbol{Z_i} + u_i > 0) \tag{3}$$

where A_i is a binary variable indicating if the farmer applied for a loan, $\boldsymbol{Z_i}$ is the exclusion restriction (represented by risk aversion Likert scale), and u_i is the error term. We use risk aversion as our exclusion restriction because this is an individual characteristic known to the farmer, but not to the bank. This implies that although risk aversion can directly affect the loan application decision, it cannot directly impact the approval decision.

The second stage is similar to Equation 2, but restricted exclusively to those farmers that were approved for loans and includes additional covariates, the inverse mills ratios, from the selection models. The second stage is presented in equation 4,

$$\begin{aligned} L_{it} = \alpha + \boldsymbol{\beta}'\boldsymbol{T1_{it}} + \boldsymbol{\theta}'\boldsymbol{T2_{it}} + \boldsymbol{\gamma}'\boldsymbol{R_t} + \boldsymbol{\delta}'\boldsymbol{X_{it}} + \pi_1\hat{\lambda}_{it} + \pi_2\hat{\lambda}_{it}R1_t + \pi_3\hat{\lambda}_{it}R2_t \\ + v_i + \epsilon_{it} \end{aligned} \tag{4}$$

where L_{it} is a binary variable (1 for approved loan and 0 otherwise), $\hat{\lambda}_{it}$ is the individual and year specific inverse mills ratio, and $\hat{\lambda}_{it}Rj_t$ is the inverse mills ratio interacted with survey rounds. The standard errors are estimated using bootstrapping with 500 repetitions and clustered at the FBO level. As usual, $\boldsymbol{\beta}'$ and $\boldsymbol{\theta}'$ provide the impact of insured loans on the outcome variables, i.e., loan approval in this case.

Finally, following recent literature, we conduct a robustness check of our results from Steps 1 and 2 by conducting an ANCOVA analysis for all our outcome variables (Table A3 in Appendix). In cases with low autocorrelation for outcomes, more power can be achieved from ANCOVA analysis rather than DID analysis (McKenzie, 2012; De Brauw et al., 2018). In contrast, if the autocorrelation is high, we should not find any statistical differences in results from earlier analyses and ANCOVA analysis.

4. Results

We begin with our primary analysis of the equilibrium impacts of insured loans on the likelihood of having a loan (Table 3). As discussed earlier, we employ three model specifications to progressively build more efficient results. Model 1 includes the treatment variables, round dummies, their interaction terms, and dummies for our stratification variables. In Model 2, we add an interaction term between round and banks with our desire to control for unforeseen challenges to credit market access because of late subsidy announcement, ethnic violence in the Upper West region, and the ending of the NRGP Program. In Model 3, we use a fixed effects model and include time-variant control variables, a savings binary variable and remittances, as discussed earlier.

Table 3 presents treatment impacts on the probability of having a loan, i.e., the equilibrium effects of insured loans on credit access for smallholder farmers. With an exception of T1 in R2, we find significant impacts of both treatments on the probability of having a loan and thus can confirm hypothesis *H3*. We predicted that when banks offer insured loans rather than uninsured loans, total credit market access increases for smallholder farmers. These impacts are 15 percentage points for micro-insured loan and 16 and 21 percentage points for meso-insured loans in R1 and R2, respectively. Even though these impacts are numerically different, a Wald test of the coefficients on both treatments for each round shows that they are not statistically different. This implies that there is no statistically significant differential impact of micro- and meso-insured loans on the probability of having loans for the farmers. Our results for meso-insured loans in Model 1 are robust to the inclusion of bank-year effects and individual-level fixed effects. Furthermore, in Models 2 and 3, there is a statistically significant difference between the point estimates for T1 and T2 in R2, suggesting that meso-insured loans may outperform micro-insured loans in their impact on credit market access. Finally, our ANCOVA analysis (see Table A3 in Appendix) demonstrates that both T1 and T2 increase the likelihood of having a loan by about 17 percentage points in R1, results that are not statistically different from our earlier models. We find no significant impacts of either treatments for R2. However, the point estimate for T2 in R2 is 0.11 with a p-value of 0.109 which is comparable to point estimates on T2 in R2 in Models 1-3.

[Table 3]

Next, we attempt to disentangle the underlying mechanisms behind increased impact of insured loans on credit access by separately estimating the treatment impacts on loan application (demand side) and approval (supply side) outcome variables. We predicted that insured loans may affect credit market access by both their effects on the behavior of farmers (credit demand) and on the behavior of banks (credit supply) in hypotheses *H1* and *H2*, respectively.

Table 4 presents the impact of treatments on loan application variable. We do not find significant impacts of either T1 or T2 on loan application rates in Model 1. Surprisingly, after controlling for bank-year effects, we find a reduction in loan application for T1 in R2. The point estimate for T2 in R2 is relatively large (0.12) and although it is insignificant, this may constitute some evidence for a positive impact of meso-insured loans on application. Based on these results we reject hypothesis *H1*. The most interesting and perplexing result for loan application rate is for T1 in R1. We predicted that T1 would increase application rate as the micro-level insurance offers borrowers the option to use the insurance payout for consumption, yet we find that the micro-insured loan may even reduce demand in R2; a result similar to Giné & Yang (2009). Using the ANCOVA analysis (see Table A3 in appendix), we find no significant impact of T1 or T2 in R1 or R2.

These results regarding the impact of insured-loans on demand for credit are mixed. Although we find one negative and significant result, the remaining point estimates are positive and insignificant. We caution that these results may not necessarily imply that insured loans reduce demand for credit or even fail to ease demand-side barriers. It may be that borrowers of micro-insured loans lower their demand for micro-insured loans in R2 because there was no payout after the first intervention; this would be consistent with "recency bias" (the bias towards recent outcomes in evaluating the probability of a shock) identified by Karlan et al. (2014). Micro-insured loan borrowers may have been affected by this because their expectation was to receive cash insurance payouts directly, rather than loan repayment. Furthermore, the remaining insignificant results could be due to several factors specific to our sample. First, our full sample is primarily composed of existing borrowers which likely means that risk rationing is already low in the full sample; the impact of insurance on application rates may be higher in the larger population. Second, we have an average application rate of 91% in R0, making it difficult to detect marginal increase from an already high application rate in the baseline (Karlan et al., 2011). Third, during the time of our treatment interventions, parts of Upper East and Upper West regions experienced ethnic violence which displaced some farmers temporarily. At the same time, the Ghanaian government ended the subsidy program and the NRGP program during our first second interventions, respectively. In fact, the coefficients on Upper East and West regions are negative and significant in Table 4.

[Table 4]

We turn next to the impact of the treatments on loan approval. Table 5 presents the treatment impacts on the loan approval variable. We find that T1 does not increase the likelihood of loan approval in R1, however the impact is significantly positive for R2. In contrast, we find a large and positive impact of T2 on loan approval, by over 20 and 15 percentage points in R1 and R2, respectively. A Wald test of the coefficients across treatments (Models 2-3) shows that meso-insured loans have a larger impact than micro-insured loans in R1, but these impacts are not statistically different in R2. As mentioned earlier, we estimated HSSM for this outcome variable due to the possibility of sample selection since only those farmers that apply for loans can be considered for loan approval; the results are presented in Model 4.[7] Using our HSSM Model, we find evidence for selection as the inverse Mills Ratio variables are jointly significant. This implies that there is a possibility of correlation between the first and second stages of selection equations and justifies the HSSM model. The estimates largely confirm those from DID and FE models (1-3) with an exception of T2 impact in R2 which is statistically significant at 10% level (Model 4) as opposed to 5% level in Models 2 and 3. Moreover, the estimations from ANCOVA analysis confirm these results with an exception of T2 impact in R2 which is marginally insignificant in the ANCOVA model with p-value just over 0.1 (Table A3 in Appendix). These findings confirm *H2* as we found that meso-insured loans increase the likelihood of loan approval by banks. Moreover, we did not place any prediction on micro-insured loans in *H2*, but we also find a positive impact of micro-insured loans on loan approval.

[Table 5]

Taken together, our results lend strong support to hypothesis *H3*. They suggest that both micro- and meso-insured loans have the potential to serve as an effective pathway to increasing credit access. When unpacking credit access into demand and supply side, we note that the positively significant impact is mainly coming from the supply side since we find positive and significant treatment impacts on loan approval (confirming hypothesis *H2*), but either negative or no impact on loan application (rejecting hypothesis *H1*). However, we note a differential impact of T1 versus T2 in R1 with statistically significant results for T2 for loan approval. There can be two possible mechanisms for such differences in the first round of treatment: (i) meso-insured loans decrease risk more for the bank because farmers can default on loans after a shock with traditional credit or micro-insured loans and (ii) the bank is more aware that the loan is insured with the meso-insured loan compared to the micro-insured loan (as modeled by Carter, Cheng & Sarris (2016)). For the former, examining the effects on default rates across treatments would give us insights on default and help us understand whether the meso-insured loan sharply reduces risk for banks (more than the micro-insured loans). However, we refrain from an explicit analysis of default for two reasons. First, there were no insurance payouts during the timeline of our experiment which means we have no opportunity to observe changes in default rates resulting from insurance payouts. Second, due to flexibility in the repayment schedule and the timing of our survey, we were unable to collect

[7] It is possible that interventions themselves change the composition of the farmers applying for each loan type. If this is the case, then we must control for interactions between the treatment variables and individual characteristics in the selection model. To do this, we first identified individual characteristics that exhibited statistical differences between loan applicants and non-applicants; we found savings and remittances (see Appendix table A2). Then we repeated model 3 from Table 4 with the addition of interaction terms between the treatments and savings and remittances. We found no interaction effect between the treatments and these individual characteristics. We therefore have no evidence that the interventions create differences in the composition of borrowers and lend support to the current specification of the HSSM presented here. These results are available upon request.

reliable measures of default.[8] Nevertheless, we do explore impacts of our treatments on default using recall data collected at baseline from FBO leaders; we find no impact of insured loans on default rate (results are available upon request).

We conjecture that the differences in T1 and T2 impacts in the first round of treatment likely stem from banks not trusting farmers to use insurance payouts for loan repayment. That is, banks fear that farmers may default on their loan and use the insurance payout to smooth consumption during a negative shock; a behavior predicted by theoretical models (Farrin & Miranda, 2015; Miranda & Gonzalez-Vega, 2011). In contrast, insurance payouts are made directly to the banks in T2, which reduces systemic risk borne by banks and results in expansion of agricultural credit supply. However, it seems that with time and experience with these insured loans, the differences across them disappear evident by the no differential impacts of T1 and T2 in the second year of treatment. For the latter, as discussed earlier, banks were aware of the insured nature of both meso- and micro-insured loans which implies that there should be no knowledge effect that is driving the differences in treatment impacts of T1 versus T2 in R2. Lastly, comparing across the models, we note that it is not surprising that we do not necessarily gain power by ANCOVA analysis over DID and FE models given loan application, approval, and *haveloan* outcome variables have higher autocorrelation in theory. In fact, this is evident by the positively significant coefficients on baseline loan application and approval variables in Appendix Table A3. Nevertheless, these results largely confirm our results from DID and FE models, indicating the robustness of our estimations.

5. Summary and Conclusions

In this paper, we investigate the role of coupling drought index insurance on equilibrium effects on agricultural credit access via a three-year RCT with two distinct treatments. In Treatment 1 (micro-insured loans), loans offered to the farmer groups are coupled with index insurance, with the contract assigned to the farmers. In Treatment 2 (meso-insured loans), loans were also offered with insurance, but with the contract assigned to the banks. Finally, in the Control group, farmer groups were provided with conventional agricultural loans without index insurance. In addition, we further investigate the pathway of impact on credit access by examining the impact of insured loans separately on loan application (demand- side) and loan approval (supply-side) outcomes.

Our results show a net positive equilibrium effect of insured loans on credit access for smallholders through higher likelihood of having a loan due to both micro- and meso-insured loans. Although we find no evidence of an increase in loan application rates (in fact a reduction for T1 in R2), the impacts of insured loans on loan approval is positive and statistically significant. Overall, we find that insured loans, be it via micro- or meso-insured loans, can overall increase credit access for smallholder farmers. Our results are consistent with theoretical literature that demonstrates that

[8] Our survey was collected during the loan repayment season. During this period, farmers may fall behind on their repayments but still repay the loan in full by the end of the season. Moreover, the bank is often flexible with repayment schedules in order to improve repayment rates. These details made it difficult for us to produce a clean default variable using our data.

insurance should improve credit market access (Carter, Cheng & Sarris, 2016; Farrin and Miranda, 2015). To the best of our knowledge, our work is unique in the literature as we observe the decision making of both the farmers and the banks. Thus, we capture a market impact of insurance on credit market access rather than on consumer decisions alone.

The related empirical literature is relatively small and confined to the impact of insurance on demand for agricultural credit. For example, using an RCT in Malawi, Giné and Yang (2009) find that weather insurance causes a lower take-up of loans, which we do find for T1 in R2. In contrast, using an RCT in Ghana, Karlan et al. (2011) find that crop price insurance has little to no impact on uptake of loans. Moreover, a recent framed field experiment in Tanzania finds that meso-insured loans increase credit demand and risk taking among smallholder farmers (Gallenstein et al, 2017). Lastly, Belissa et al (2018) examine the impact of delayed premium payment on weather insurance take-up in Ethiopia and find that it results in increased demand. In our data, we find no statistically significant impact of drought-based index insurance on loan application likelihood of farmers. These results are in the middle of the spectrum of the limited literature on credit demand and is similar to those of Karlan et al. (2011). As mentioned earlier, our study is the first to provide empirical evidence on the supply of credit as measured in the loan approval decision. Our empirical results on loan approval are broadly consistent with theoretical models predicting that insured loans improve supply of credit (Carter. Cheng & Sarris; Farrin & Miranda, 2015; Miranda & Gonzalez-Vega, 2011). However, our results that micro-insured loans improve loan approval to a similar extent as meso-insured loans contradict Miranda & Gonzalez-Vega (2010) who predicted that micro-insured loans would de-stabilize microfinance banks due to increased strategic default in the long run.

From our equilibrium effects analysis, we find that insuring agricultural loans in a way that guarantees full loan repayment during a drought expands credit access for smallholders. This is evidenced by both micro- and meso-insured loans spurring a quantitatively large increase of about 15 and between 15 to over 20 percentage points in the likelihood of having a loan for farmers, respectively. This finding is largely robust across all model specifications suggesting important policy implications. When risk reducing mechanisms, such as micro- and meso-insured loans, are integrated into the borrower's and lender's portfolios, it can increase credit access in developing countries.

We further demonstrate that these impacts on credit access stem largely from the impact of the insured loans on the supply of credit. We do not find a significant positive impact of insured loans on demand for credit (although a large point estimate for meso-insured loans in round two suggests some positive effect of meso-insured loans) and in fact, in round two, we find that micro-insured loans reduce demand for credit. The largely insignificant results may be due to issues we discussed earlier: our sample is primarily composed of existing borrowers indicating low risk rationing as already compared to the larger population (the baseline application rate is 91%), making it difficult to detect marginal increase from an already high application rate (Karlan et al., 2011), parts of Upper East region faced ethnic violence, the Ghanaian government ended its agricultural subsidy program after the baseline survey, and ended the Northern Rural Growth Programme after the follow-up survey. Lastly, we find that both micro- and meso-insured loans increase the likelihood of loan approval by banks; a result that bolsters theoretical arguments that risk reducing mechanisms can crowd in agricultural loan supply (Farrin & Miranda, 2015).

Furthermore, the finding that meso-insured loans have a more significant and positive impact on loan approval versus micro-insured loans may further indicate some distrust between banks and farmers (Cai et al., 2014; Cole et al., 2013) and that loan repayment in a systemic shock state with micro-insured loans may not be incentive compatible. Therefore, we caution that the provision of insured loans themselves may not be a sufficient condition for increasing credit access, rather, factors such as contract design and trust matter. For example, insured loans coupled with an income insurance such that farmers (banks) can use (give) part of the payout for consumption smoothing can protect the most vulnerable farmers from defaulting in case of a drought and may boost credit demand (Farrin and Miranda, 2015). Alternatively, a contract with delayed premium until after the harvest can ease liquidity constraint and encourage demand (Belissa et al., 2018). Likewise, demand for meso-insured loans may increase if banks respond to insurance by lowering interest rates, a result predicted by Carter et al. (2016) and Farrin and Miranda (2015). Indeed, one of our partner banks lowered interest rates for meso-insured loans after our study. That said, this merits further investigation.

Although our results suggest that index insurance, by easing systemic risk on lenders, can improve agricultural credit supply, we caution that these findings cannot be easily assumed to be externally valid to other populations or locations. These results are specific to our select sample of smallholder clients of rural and community banks in northern Ghana. For this reason, we conform with an emerging practice in the literature and speculate on the external validity of our experimental results (Banerjee et al., 2017; Dupas, 2014). We believe that our results stem from certain underlying mechanisms that may be used to predict validity in other contexts and serve as basis for future research. The mechanisms include the following: (i) the risk of systemic shocks prevent borrowers from applying for formal agricultural credit and (ii) the risk of systemic shocks restrain banks from extending credit to smallholder farmers. When it comes to the supply-side mechanism, we believe that our results will extend to contexts in which banks lend to farmers with a moderate to high risk of systemic weather-related shocks to production. However, since we did not find a robust evidence of credit rationing on supply side (evidenced by 91% application rate in baseline round and all farmers being either existing or potential clients of the banks), we predict that in environments with populations of non-borrowers who have previously been risk-rationed from the formal credit market entirely, insured loans may increase demand for credit.

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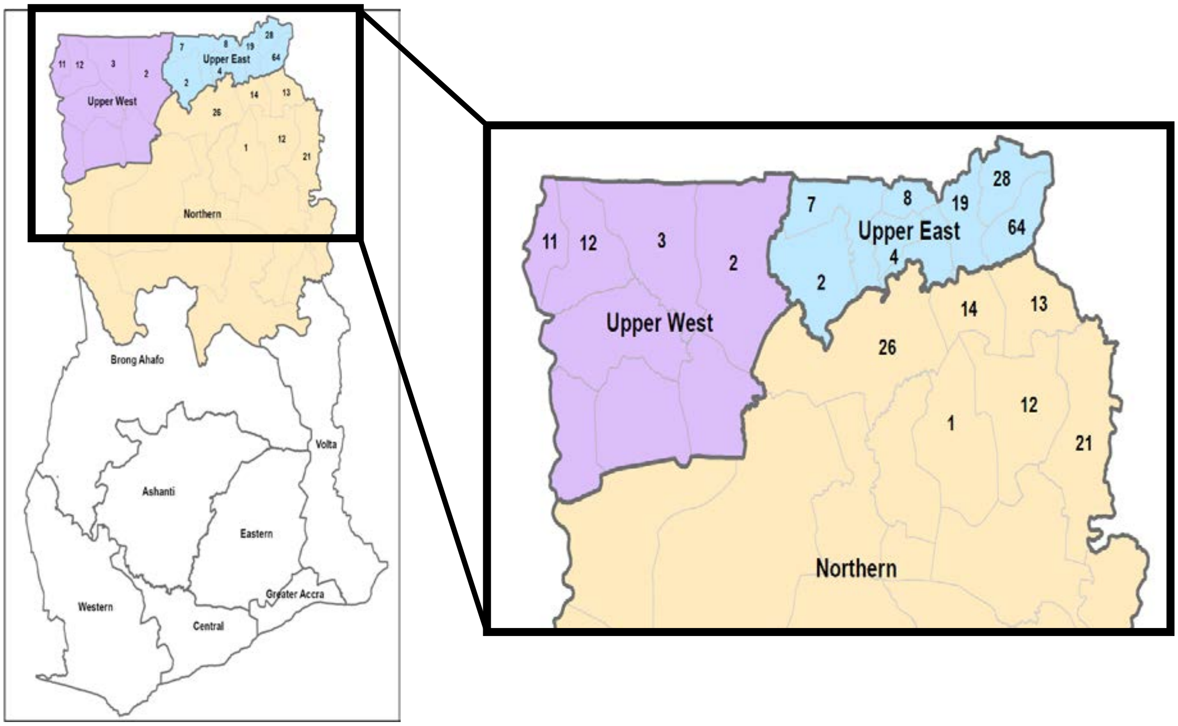
Figures and Tables

Figure 1. Map of Study Area in Northern Ghana



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

Figure 2: Randomized Control Trial Process Map

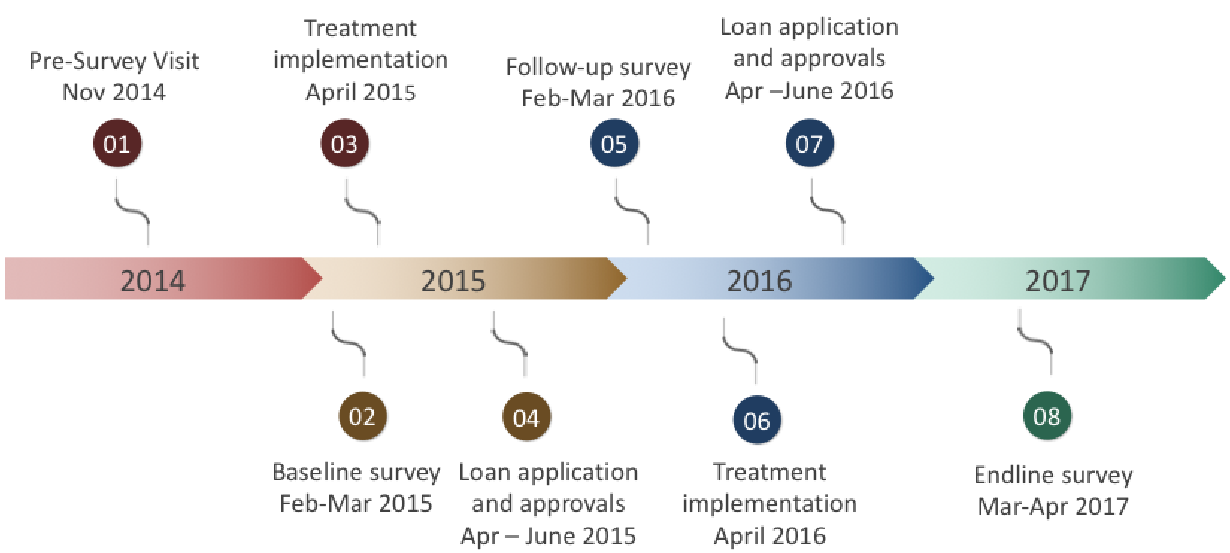


Table 1. Sample Means and Standard Deviations of Key Variables by Survey Round

	Baseline (R0)		Follow-up (R1)		Endline (R2)	
Variable	Mean	Std.	Mean	Std.	Mean	Std.
Have a loan	0.70	0.46	0.63	0.48	0.36	0.48
Loan application	0.91	0.28	0.80	0.40	0.57	0.50
Loan approval	0.76	0.43	0.79	0.41	0.63	0.48
Has savings (1=yes)	0.68	0.47	0.79	0.41	0.71	0.46
Debt (1=outstanding debt)	0.20	0.40	0.32	0.47	--	--
Land planted with maize (acres)	2.9	3.6	2.7	2.8	2.6	3.2
Maize yield	326	216	346	216	361	215
Maize revenue	883	1240	1023	1282	917	1243
Loan size	321	246	415	244	444	353
No. of plots used	3.0	1.0	3.9	2.0	--	--
Cattle	4.0	7.0	3.2	4.0	3.1	6.5
Remittances (GH₵)	100	204	124	223	97	193
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	2.4	0.9	2.5	0.8	2.6	0.9

Notes: Savings is a binary variable indicating whether farmers have savings with the bank; drought help is the number of people the farmer can get help from in case of drought.

Table 1. Sample Proportions of Key Variables

Variable	Proportion
Risk aversion	
Very willing to take risk	0.32
Willing to take risk	0.40
Indifferent to taking risk	0.12
Not willing to take risk	0.15
Not at all willing to take risk	0.01
Borrower status in 2014	
Non-borrower	0.27
Borrower	0.73
Respondent gender	
Male	0.53
Female	0.47
Respondent education	
Less than primary education	0.78
Primary education	0.05
Middle school	0.06
High school	0.07
College or more	0.04

Notes: Risk aversion is a 5-point Likert scale measured during baseline.

Table 2. Means of Selected Outcome Variable by Survey Round

Outcome Variable	Uninsured (C)	Micro-insured (T1)	Meso-insured (T2)
Have a Loan Outcome Variable			
Loan Application R0	0.707	0.736	0.649
Loan Application R1	0.521	0.701***	0.676***
Loan Application R2	0.310	0.349	0.411**
Loan Application Outcome Variable			
Loan Application R0	0.919	0.931	0.896
Loan Application R1	0.757	0.851***	0.792
Loan Application R2	0.578	0.479**	0.643
Loan Approval Outcome Variable			
Loan Approval R0	0.769	0.790	0.724
Loan Approval R1	0.689	0.824***	0.854***
Loan Approval R2	0.537	0.728***	0.639*

Notes: *** p<0.01, ** p<0.05, * p<0.1; R0, R1, and R2 indicate baseline, follow-up, and endline rounds, respectively; non-borrowers are those farmers with 2014 borrower status=0.

Table 3. Linear Probability Model Treatments Impacts on Haveloan Variable

Variable	Model 1	Model 2	Model 3
Round 1	-0.185***	-0.371***	-0.209***
	(0.063)	(0.122)	(0.075)
Round 2	-0.398***	-0.363***	0.010
	(0.057)	(0.134)	(0.083)
Treatment 1	0.025	-0.006	
	(0.050)	(0.052)	
Treatment 2	-0.063	-0.096	
	(0.053)	(0.053)	
Treatment1*Round1	0.151*	0.124	0.126
	(0.085)	(0.079)	(0.079)
Treatment1*Round2	0.011	-0.019	-0.015
	(0.087)	(0.083)	(0.083)
Treatment2*Round1	0.212**	0.203***	0.202***
	(0.084)	(0.075)	(0.075)
Treatment2*Round2	0.160*	0.173**	0.174**
	(0.087)	(0.082)	(0.082)
Bank saving binary (1=yes)			-0.012
			(0.025)
Remittance/100 (GH₵)			0.004
			(0.005)
Previous borrower (1=yes)	0.415***	0.290***	
	(0.036)	(0.033)	
Upper East region	-0.028	0.002	
	(0.038)	(0.062)	
Upper West region	-0.013	-0.450***	
	(0.061)	(0.138)	
Late on payments in 2014		-0.352***	
		(0.030)	
Constant	0.421***	0.743***	0.503***
	(0.049)	(0.048)	(0.038)
Bank-level dummies	No	Yes	Yes
Observations	2335	2335	2332
R-squared	0.235	0.370	0.141
Number of HHID			779

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered at group level and are in parentheses. Round1 indicates follow-up, Round 2 indicates endline, 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; Banks have been interacted with rounds to be included as dummies; Models 1 and 2 are DID and 3 is FE; Previous borrower=1 for those borrowing before 2014.

Table 4. Linear Probability Model Treatments Impacts on Loan Application

Variable	Model 1	Model 2	Model 3
Round 1	-0.162***	-0.100	-0.063
	(0.052)	(0.090)	(0.070)
Round 2	-0.341***	-0.247*	0.133*
	(0.059)	(0.126)	(0.073)
Treatment 1	0.015	0.003	
	(0.040)	(0.038)	
Treatment 2	-0.026	-0.046	
	(0.044)	(0.041)	
Treatment1*Round1	0.082	0.072	0.074
	(0.066)	(0.063)	(0.063)
Treatment1*Round2	-0.111	-0.142*	-0.137*
	(0.079)	(0.073)	(0.073)
Treatment2*Round1	0.058	0.058	0.057
	(0.072)	(0.070)	(0.069)
Treatment2*Round2	0.089	0.115	0.119
	(0.083)	(0.082)	(0.082)
Bank saving binary (1=yes)			-0.015
			(0.023)
Remittance/100 (GH₵)			0.004
			(0.005)
Previous borrower (1=yes)	0.064*	-0.004	
	(0.038)	(0.041)	
Upper East region	-0.093***	-0.072	
	(0.036)	(0.049)	
Upper West region	-0.159**	-0.608***	
	(0.067)	(0.169)	
Late on payments in 2014		-0.165***	
		(0.044)	
Constant	0.937***	1.010	0.627
	(0.042)	(0.046)	(0.032)
Bank-level dummies	No	Yes	Yes
Observations	2,335	2,335	2,332
R-squared	0.146	0.270	0.078
Number of HHID			779

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Round1 indicates follow-up round, Round 2 indicates endline, 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; Banks have been interacted with rounds to be included as dummies; Models 1 and 2 are DID and 3 is FE; Previous borrower=1 for those borrowing before 2014.

Table 5. Linear Probability Model Treatments Impacts on Loan Approval

Variable	Model 1	Model 2	Model 3	Model 4
Round 1	-0.086	-0.375	-0.078	0.077
	(0.069)	(0.13)	(0.082)	(0.074)
Round 2	-0.209***	-0.173	-1.020***	-0.095
	(0.063)	(0.083)	(0.102)	(0.082)
Treatment 1	0.014	0.027		
	(0.043)	(0.046)		
Treatment 2	-0.052	-0.110		
	(0.044)	(0.047)		
Treatment1*Round1	0.130	0.104	0.091	0.037
	(0.087)	(0.081)	(0.082)	(0.086)
Treatment1*Round2	0.171*	0.167*	0.214**	0.266***
	(0.094)	(0.094)	(0.098)	(0.096)
Treatment2*Round1	0.230***	0.241***	0.213***	0.217***
	(0.084)	(0.074)	(0.073)	(0.083)
Treatment2*Round2	0.150	0.204**	0.172**	0.167*
	(0.093)	(0.083)	(0.085)	(0.098)
Bank saving binary (1=yes)			-0.015	-0.033
			(0.027)	(0.028)
Remittance/100 (GH₵)			0.005	-0.011**
			(0.005)	(0.005)
Previous borrower (1=yes)	0.495***	0.370***		
	(0.039)	(0.033)		
Upper East region	0.039	0.078		
	(0.033)	(0.062)		
Upper West region	0.095*	-0.439***		
	(0.057)	(0.094)		
Late on payments in 2014		-0.333***		
		(0.036)		
Constant	0.368***	0.683***	1.262***	
	(0.049)	(0.047)	(0.054)	
Bank-level dummies	No	Yes	Yes	No
Observations	1776	1776	1775	1775
R-squared	0.290	0.329	0.174	
Number of HHID			752	752
Chi-square Joint Test on IMRs				20.9***
Rho				0.501

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Round1 indicates follow-up round, Round 2 indicates endline, 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; Banks have been interacted with rounds to be included as dummies; Models 1 and 2 are DID and 3 is FE; Previous borrower=1 for those borrowing before 2014.

Appendix

Table A1. One-way Analysis of Variance (ANOVA) across Control and Treatment Categories

Category	Mean	Std.	P-Value
Maize quantity (KGs)			0.18
Control	1,152	2,260	
Treatment 1	1,326	4,755	
Treatment 2	816	989	
Fertilizer quantity (Packet)			0.53
Control	10.4	0.35	
Treatment 1	7.4	0.35	
Treatment 2	6.6	0.34	
Hybrid binary (1=use)			0.81
Control	0.15	0.35	
Treatment 1	0.15	0.36	
Treatment 2	0.13	0.34	
Number of loans taken from formal and informal sources			0.84
Control	0.66	0.63	
Treatment 1	0.63	0.62	
Treatment 2	0.64	0.62	
Default binary (1=defaulted)			0.84
Control	0.16	0.37	
Treatment 1	0.15	0.36	
Treatment 2	0.17	0.38	
Total income (GH₵)			0.62
Control	2,269	1,592	
Treatment 1	2,210	1,441	
Treatment 2	2,141	1,434	
Agricultural income (GH₵)			0.52
Control	1,453	1,002	
Treatment 1	1,426	941	
Treatment 2	1,351	935	
Time taken to input market (Minutes)			0.78
Control	83.5	83.1	
Treatment 1	80.7	69.4	
Treatment 2	85.9	101.0	
Aggregator binary (1=sell via aggregator)			0.59
Control	0.36	0.48	
Treatment 1	0.40	0.49	
Treatment 2	0.36	0.48	
Good season (1=2014 was a good season)			0.91
Control	0.40	0.49	
Treatment 1	0.42	0.49	
Treatment 2	0.40	0.49	
Risk aversion (Likert Scale 1-5)			0.67
Control	2.1	1.1	
Treatment 1	2.1	1.0	
Treatment 2	2.2	1.1	
Maize planted land (Acres)			0.30
Control	2.9	3.1	

Treatment 1	3.1	4.8	
Treatment 2	2.6	2.4	
Number of household members			0.30
Control	8.6	3.2	
Treatment 1	8.4	3.3	
Treatment 2	8.2	3.4	
Medical emergency (frequency)			0.47
Control	3.1	4.3	
Treatment 1	2.6	4.3	
Treatment 2	2.7	4.1	
Borrow cash/in-kind (frequency)			0.55
Control	0.57	0.99	
Treatment 1	0.62	1.00	
Treatment 2	0.52	0.99	
Death (frequency)			0.95
Control	0.44	0.85	
Treatment 1	0.43	0.77	
Treatment 2	0.45	0.86	
Festival (frequency)			0.89
Control	0.87	1.30	
Treatment 1	0.86	1.30	
Treatment 2	0.82	1.30	
Crop loss (frequency)			0.57
Control	0.32	0.94	
Treatment 1	0.32	0.67	
Treatment 2	0.26	0.54	
Cash loan (1=prefer loan in cash)			0.36
Control	0.56	0.50	
Treatment 1	0.50	0.50	
Treatment 2	0.52	0.50	
Price of maize (GH₵/ KG)			0.25
Control	1.00	0.43	
Treatment 1	1.04	0.41	
Treatment 2	0.98	0.35	
Remittance (GH₵)			0.27
Control	115	0.44	
Treatment 1	100	0.41	
Treatment 2	86	0.35	
Proportion of plots planted with maize			0.33
Control	0.42	0.22	
Treatment 1	0.42	0.24	
Treatment 2	0.45	0.40	
District			0.46
Control	11	6.6	
Treatment 1	12	7.3	
Treatment 2	11	6.8	

Table A2. Pairwise Mean T-test Comparisons for Key Variables by Application/Approval Status for Baseline Round (R0)

Variable	Apply	Did not Apply	Difference
Agric. Inc. (GHc)	1,543	1,401	
No. of plots used	3.2	3.0	
Cattle	4.4	4.0	
Remittances (GHc)	39	106	**
Saving binary	0.57	0.68	*
Respondent age	44	45	
Drought help	2.2	2.0	
No. of last 5 good seasons	2.3	2.4	
Debt (1=outstanding debt)	0.23	0.20	
	Approve	Reject	Difference
Agric. Inc. (GHc)	1,471	1,379	
No. of plots used	2.8	3.0	**
Cattle	5.1	3.6	**
Remittances (GHc)	82	113	*
Saving binary	0.72	0.67	
Respondent age	45	45	
Drought help	1.8	2.0	
No. of last 5 good seasons	2.4	2.4	
Debt (1=outstanding debt)	0.25	0.18	**

Notes: *** p<0.01, ** p<0.05, * p<0.1. No. of plots used represents plots used for farming; Savings binary is 1 if the farmers report having savings with the bank; Drought help is the number of people the farmer can get help from in case of drought; Good season 5 represents how many of the past 5 seasons the farmer thinks was a good season; Risk aversion is a 5-point Likert-Scale measured during baseline; and Debt is whether the farmer has an outstanding debt from last season.

Table A3: Analysis of Covariance (ANCOVA) for Treatment Impacts on Outcome Variables by Round

	Haveloan		Apply		Approve	
Variable	Round 1	Round 2	Round 1	Round 2	Round 1	Round 2
Treatment 1	0.168**	0.033	0.092	-0.100	0.080	0.184**
	(0.070)	(0.069)	(0.059)	(0.072)	(0.071)	(0.088)
Treatment 2	0.177**	0.111	0.039	0.072	0.189***	0.132
	(0.070)	(0.069)	(0.062)	(0.074)	(0.066)	(0.082)
Haveloan_0	0.388***	0.193**				
	(0.085)	(0.080)				
Apply_0			0.276**	0.317***		
			(0.107)	(0.098)		
Approve_0					0.359***	0.307**
					(0.092)	(0.137)
Previous borrower	-0.020	0.053	0.065	-0.048	-0.069	0.080
	(0.083)	(0.076)	(0.056)	(0.064)	(0.075)	(0.130)
Upper East region	-0.139**	-0.044	-0.154***	-0.211***	-0.049	0.114
	(0.058)	(0.063)	(0.050)	(0.065)	(0.052)	(0.078)
Upper West region	0.023	-0.027	-0.140	-0.171*	0.190***	0.127
	(0.091)	(0.095)	(0.089)	(0.103)	(0.050)	(0.111)
Constant	0.330***	0.160**	0.549***	0.447***	0.500***	0.220***
	(0.078)	(0.063)	(0.113)	(0.111)	(0.094)	(0.084)
Observations	779	777	779	777	587	418
R-squared	0.153	0.056	0.081	0.086	0.149	0.178

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Round1 indicates follow-up round, Round 2 indicates endline; Treatment 1 and Treatment 2 indicate micro- and meso-insured loans, respectively; Uninsured loan (C) has been excluded from the dummy; Have-a-Loan_0, Apply_0, and Approve_0 indicate having a loan, application, and approval outcomes in the baseline, respectively; Previous borrower=1 for those borrowing before 2014.