You are Approved!

Insured Loans Improve Credit Access and Technology Adoption of Ghanaian Farmers

by

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Abstract

Increasing agricultural efficiency via technology adoption remains a high priority among development practitioners. One potential tool for furthering this objective is using drought index insurance to increase access to credit. Accordingly, the objective of this paper is to investigate whether coupling agricultural loans with micro-level and meso-level drought index insurance can stimulate the demand and supply of credit and increase technology adoption. To this end, in partnership with 14 rural banks and the Ghana Agricultural Insurance Pool, we implemented a randomized control trial in northern Ghana that targeted maize farmers organized in credit groups. Our empirical analysis indicates that coupling loans with meso-insurance increases the likelihood of loan approval by 23 percentage points. Gender-level analysis shows that micro-insurance-coupled loans increase the likelihood of loan application for females while meso-insurance-coupled loans increase the likelihood of loan approval for both females and males, but with a larger impact for males. Overall, our results indicate that insured loans hold significant promise for expanding credit access and technology adoption among smallholder farmers.

Key words: credit access, drought index insurance, randomized control trial, Northern Ghana

[1] Corresponding author. Email: mishra.67@osu.edu. This research was partly funded by a USAID/BASIS grant. We are grateful to the participants in the 2015 BASIS technical Meeting at UC Berkley and the PhD Seminar in Agricultural, Environmental, and Department Economics at the Ohio State University for their feedback. The usual disclaimer applies.

1. Introduction

Increasing agricultural efficiency is key to reducing poverty in developing agrarian economies such as those in Sub-Saharan Africa (SSA). The agricultural sector accounts for over half of total employment and one-fifth of gross domestic product (GDP) in SSA (International Monetary Fund 2012). The difference between agricultural employment and contribution to GDP indicates comparatively low labor productivity within the sector. Labor productivity is held back primarily by low rates of adoption and retention of improved production technologies, such as improved seeds (Doss 2006; Feder, Just, and Zilberman 1985; Sunding and Zilberman 2001). These technologies are critical for reducing rural poverty and improving household well-being in these economies (Bourdillon et al. 2003; Mendola 2007; Kijima, Otsuka, and Sserunkuuma 2008; Kassie, Shiferaw, and Muricho 2011). Yet, SSA countries have among the lowest rates of technology adoption in the world (Tripp and 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 and Udry 2010; Duflo, Kremer, and Robinson 2008; Foster and Rosenzweig 1995). Central to the barriers of adoption are two interrelated factors: (i) poor access to credit, particularly to overcome any lumpiness of investment and (ii) the riskiness of agricultural returns, primarily due to systemic weather shocks (Farrin and Miranda 2015).

These barriers affect both farmers' demand and banks' supply of agricultural credit. On the demand side, farmers are often reluctant to seek credit due to the risk of losing their assets pledged as collateral in the case of a failure to repay; a phenomenon called risk-rationing (Hertz 2009; Mude and Barrett 2012). This is particularly true for female headed households owing to their lack of access and ownership of agricultural resources, fewer avenues to insure themselves against systemic shocks, credit constraints, and higher risk aversion (Fletschner, Anderson, and Cullen 2010; Khandker 1998; Mishra and Sam 2016; Quisumbing and Pandolfelli 2010). The low adoption rates among females pose a significant barrier to agricultural efficiency improvements since females make up 50% of the SSA agricultural labor force (Food and Agriculture Organization of the United Nations (FAO) 2011). For example, female farmers in Ethiopia and Malawi have roughly 23-30% lower agricultural labor productivity than their male counterparts (Aguilar et al. 2015; Kilic, Palacios-López, and Goldstein 2015). Leveling the playing field of access to agricultural resources, including technology, between female and male farmers could increase total global agricultural output by 4% and reduce world hunger by between 12 and 17% (FAO 2011).

Mechanisms that reduce the risk of default during systemic events can spur higher demand of agricultural credit and attendant technology adoption among female farmers.

On the supply side, widespread systemic weather events (e.g., drought and floods), which have become more common due to climate change, increase the variability of agricultural returns (FAO 2016), thereby exposing lenders to substantial undiversifiable systemic risk. This can be particularly damaging for male farmers who are seen as less creditworthy due to their lower repayment records. For example, 92% of females paid on time, compared to 83% of males in Malawi, and only 1.3% of the Grameen female borrowers had repayment problems, compared to 15.3% of male borrowers in Bangladesh (Hulme 1991; Khandker, Khalily, and Khan 1995). Similarly, credit groups with higher percentages of females had significantly better repayment rates in Bangladesh and Guatemala (Sharma and Zeller 1997; Kevane and Wydick 2001). Finally, using data from 350 microfinance institutions from over 70 countries, D'Espallier, Guérin, and Mersland (2011) find that female clients are associated with lower portfolio risk, fewer write-offs, and higher repayment rates. Thus, mechanisms that remove the downside risks of defaults during systemic events may reduce supply-side barriers and encourage adoption among male farmers.

In light of these challenges, a carefully designed drought index insurance (DII) product, when properly integrated into the financial market, may reduce the riskiness of agricultural returns in case of a drought and improve access to credit. DII pays out based on the observation of an objective rainfall index such as measures of precipitation from rainfall stations or satellite data. Relying on an exogenous index allows the insurer to avoid high transaction costs associated with indemnity insurance (e.g., the cost of assessing and validating individual policy holders' losses) and informational asymmetry problems (e.g., moral hazard and adverse selection). Hence, DII 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 its expected benefits, early initiatives have seen limited uptake of DII by smallholder farmers in absence of substantial subsidization, be it as individual contracts or coupled with loans (Cole et al. 2013; Giné and Yang 2009; Karlan et al. 2011).

The limited uptake of DII has been attributed 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 (Cole et al. 2013; Giné and Yang 2009; Jensen, Barrett, and Mude 2014). Most of these issues can be mitigated by a better designed product. In this regard, a novel use 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) has been recently proposed

(Carter, Cheng, and Sarris 2011; Miranda and Gonzalez-Vega 2010). Theoretical models have predicted that such a product can reduce the risk of defaults and improve farmer's creditworthiness, credit sustainability, and technology adoption (Farrin and Miranda 2015; Miranda and Gonzalez-Vega 2010). This can particularly encourage credit approval for male framers who are otherwise seen as riskier due to higher defaults. Likewise, the insurance protection afforded to smallholders in case of a systemic event may encourage the risk-rationed farmers (e.g., female farmers) to seek credit that they otherwise would have avoided. Thus, meso-level index insurance has the potential to boost technology adoption among smallholder farmers. However, there is a lack of robust empirical evidence to support these predictions. Moreover, to the best of our knowledge, there are no studies that explore the differential impacts of micro- and meso-insurance on credit access and technology adoption, and none that explores their gender impacts.

In light of these gaps in the literature, the objectives of our paper are: (i) 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 the supply and demand of smallholder agricultural credit and advanced technologies; (ii) to investigate if these impacts are higher for female farmers on the demand side (due to higher risk-rationing of females) and male farmers on the supply side (due to bank's perception of males as less creditworthy).

Our research methodology employs a simple theoretical model and a randomized control trial (RCT) in northern Ghana to test the model predictions. Using micro- and meso-insured loans as separate treatments and the provision of conventional uninsured loans as the control, results of our difference-in-differences analysis indicate three major findings. First, for the total sample, we find that there is no impact of insured loans on farmers' loan application probabilities. This maybe because our sample is composed of farmers who have been applying for loans with the banks for years with pre-treatment application rates as high as 90%. Second, we find that banks are more likely to approve loans for farmers by 23 percentage points with meso-insured loans. Third, for the gender disaggregated sample, we find that (i) the loan application probability for female farmers increases with micro-insured loans; and (ii) the loan approval probability increases for both female and male farmers with meso-insured loans. Moreover, the approval probability is higher for male farmers, compared to female farmers. Overall, our findings suggest that index insured loan products can simultaneously reduce both supply-side and demand-side credit constraints, thereby increasing credit access and technology adoption in areas with predominantly smallholder farmers.[2]

The remainder of the paper is structured as follows. Section 2 provides a brief background of the agricultural sector in Ghana. Section 3 provides a theoretical framework. Section 4 discusses the experimental design and descriptive statistics of our study sample. Section 5 presents the empirical framework and results. Section 6 concludes.

2. Background

As is the case for many SSA countries, 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). In particular, 65% of the female-headed households and 44% of the male-headed households are farming households who make up 30 and 70% of total farmers, respectively (FAO 2012). In addition to the mismatch between the share of GDP and employment, there is also a mismatch between the share of expenditure and GDP growth rate in agriculture. For example, the share of total public expenditure allocated to the food and agriculture sector increased from 2007 to 2013, but the share of agricultural GDP decreased during this period (Food and Agriculture Policy Decision Analysis 2015). These inefficiencies in the Ghanaian agricultural sector are a result of the high proportion of smallholder farmers using traditional rainfall dependent production systems (Ministry of Food and Agriculture (MOFA) 2011). For example, agricultural technologies such as inorganic fertilizer and certified seeds are used by only 29 and 16% of the population, respectively (Ghana Statistical Service 2014). Female farmers have even lower use of agricultural technologies compared to male farmers (Doss and Morris 2000). A primary reason for the low levels of adoption of improved production technologies is lack of access to credit (Nair and Fissha 2010).

The Ghanaian government has made efforts to increase access to agricultural finance by establishing an agricultural lending requirement for commercial banks, creating a publicly owned agricultural development bank, and facilitating the establishment of rural and community banks (RCBs) (Nair and Fissha 2010). The RCBs were established to solve the issue of high interest rates charged by moneylenders and traders, and provide rural communities with secure, safe, and convenient savings and payment facilities. The first RCB was established in 1976 in a farming community in the central region of

[2] The credit provided to the farmers is mostly in-kind such as bags of fertilizer, improved seeds, and modern ploughing services. This implies that an increase in access to credit is an increase in technology adoption.

Ghana. 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 (Nair and Fissha 2010).

In 1981, the RCBs formed an Association of Rural Banks (ARB) as a networking forum that promotes, represents, and provides training services to its member RCBs. The 16 RCBs in the three northern regions of Ghana (Northern, Upper East, and Upper West) operate under the ARB-Northern Ghana Chapter. These banks are chartered to operate within a particular region with generally one ethnic/language group (Nair and Fissha 2010). The RCBs primarily provide loans to farmers in groups, which are formed by farmers organically or facilitated by extension agents working for MOFA.[3] Once these farmer groups (FGs) are formed, they must meet the following criteria to apply for loans: open savings accounts with the banks, be functional, follow bylaws, and conduct regular meetings with proof of minutes. To apply for a loan, FGs are required to prepare a budget for agricultural inputs usually with the help of extension agents or other related non-governmental organizations.

In addition to credit constraints, another major factor affecting the Ghanaian agriculture is climate change. Mean daily temperatures in Ghana are expected to increase by between 2.5 and 3.0 degree Celsius, while rainfall is expected to decline between 9 and 27% by the year 2100 (Ghana Insurers Association 2015). The changing climate imposes the highest risk on smallholder farmers whose livelihoods depend on agriculture. The Ghana Agricultural Insurance Pool (GAIP) was established in March 2010 to provide economically sustainable agricultural insurance that protect farmers, agro-processors, rural and financial institutions, and input dealers during droughts. Currently, GAIP primarily offers drought insurance policies for maize and soy crops.

3. Theoretical Model

In this section, we formalize the impacts of insured loans on farmers' loan application and approval rates by developing a simple theoretical model based on Giné and Yang (2009)'s. However, our model differs from theirs in four important ways. First, we do away with their illiquid collateral assumption since we are dealing with group lending in this paper; instead we add φ, which is the present value of future consumption afforded by being a creditworthy borrower. We call this "creditworthiness". Second, we explore separate impacts of micro- versus meso-level insured loans on credit access. Third, we consider

[3] The requirements to create a farmer group are that the members must be from the same community, are mostly of the same communal labor group, and know each other well. The criteria were provided by the RCBs in northern Ghana.

these impacts from the lender's perspective in addition to the borrower's. Finally, we propose gender differential impacts of insured loans from supply and demand sides.

Assume a representative subsistence farmer who grows a crop using an improved technology. This technology gives higher yields Y_H, with probability p in a good rainfall state and lower yields Y_L, with probability $1-p$ in a drought state.[4] With no liquid wealth, the farmer needs an in-kind loan K, to invest in the improved technology, which must be repaid with an interest rate r. As such, $R=(1+r)K$ is the amount owed to the bank upon harvest. Banks practice group lending so they do not require any physical asset as collateral. However, each farmer is characterized by φ, a measure of creditworthiness defined earlier. Therefore, increases in φ means decreases in the probability that farmers will default, other things being equal. We assume that $\varphi \in (R, \frac{R}{p})$.

We assume that $Y_H \gg Y_L$ and that a good state output is more than enough to cover the repayment amount R and the farmer continues to enjoy φ, but a drought state output is not enough for repayment and φ becomes zero. As such, in a good rainfall event, the consumption of the farmer is $C_H = Y_H - R + \varphi$ and in a drought event, it is $C_L = Y_L$. The farmer's utility is simply a function of consumption. Therefore, the expected utility of adopting the high technology with an uninsured loan, U_U, is:

$$U_U = pu(Y_H - R + \varphi) + (1-p)u(Y_L) \tag{1}$$

Suppose that banks offer an insured loan such that in a drought event, the insurance pays out the loan principal and interest including the premium π. Thus, the insurance pays out the insured loan repayment amount, $R^I = (1+r)(K+\pi)$, in the case of a drought. If the premium is actuarially fair, then $(1+r)\pi = (1-p)R^I$ and hence, $\pi = \frac{1-p}{p}K$. Furthermore, we can express the amount to be repaid under the insured loan as a function of the amount to be repaid under the uninsured loan as $R^I = \frac{R}{p}$ (see Appendix for step by step calculations).

Suppose there are two types of insured loan contracts, one in which the payouts are given to the farmers (micro-insured loans) and another in which the payouts are given to the banks (meso-insured loans) such that the bank uses these payouts to fully forgive the loans in case of a drought. Assume that the farmer always repays in a good state. With the micro-insured loans, the farmer gets a payout in a drought state and has the choice to either repay or not. If the farmer repays, her consumption in a bad

[4] Although farmers in our study sample borrow in groups, for the sake of simplicity, we assume that group members within a group are homogeneous and hence the whole group behaves like a single representative farmer.

state is $Y_L + \varphi$ but if she does not then her consumption is $Y_L + \frac{R}{p}$. Since $\varphi < \frac{R}{p}$, the farmer should strategically default as such her expected utility from a micro-insured loan, U_{IC}, can be expressed as:

$$U_{IC} = pu\left(Y_H - \frac{R}{p} + \varphi\right) + (1-p)u(Y_L + \frac{R}{p}) \tag{2}$$

For the meso-insured loans, the payout is given directly to the bank such that the farmer does not have an option to default in a drought state. Thus, the expected utility of the farmer from a meso-insured loan, U_{BC}, can be expressed as:

$$U_{BC} = pu\left(Y_H - \frac{R}{p} + \varphi\right) + (1-p)u(Y_L + \varphi) \tag{3}$$

Comparing Equations 1-3,

$$U_{IC} > U_{BC} > U_U \tag{4}$$

Therefore, from a farmer's perspective, micro-insured loans provide the highest level of utility, followed by meso-insured loans, compared to uninsured loans[5].

Now turning to the lender's perspective, we assume that lenders do not observe the probability of the farmer's repayments. However, the lenders know that the higher the farmer's creditworthiness, the higher the likelihood of repayment. Therefore, the lender's probability of receiving repayments, p^*, is a function of φ that maps to $(0, 1)$ and $\frac{\partial p^*}{\partial \varphi} > 0$. Normalizing the number of potential borrowers to 1, the expected profit for a bank from an uninsured loan, $\prod_U$, is given by:

$$\prod\nolimits_U = p^*(\varphi)R \tag{5}$$

For the micro-insured loan, we add a probability q of repayment in a bad state to capture the lender's uncertainty regarding borrowers decision to strategically default with insurance payout. The expected profit from a micro-insured loan, $\prod_{IC}$, is given by:

$$\prod\nolimits_{IC} = \ p^*(\varphi)R + (1 - p^*(\varphi))qR \tag{6}$$

For meso-insured loans, since there is no strategic default, the expected profit from an insured loan, $\prod_{BC}$, is given by:

$$\prod\nolimits_{BC} = R \tag{7}$$

Comparing Equations 5-7 , for $p^* < 1$ & $0 < q < 1$, we have:

$$\prod\nolimits_{BC} > \prod\nolimits_{IC} > \prod\nolimits_U \tag{8}$$

Therefore, lender profits are highest with meso-insured loans, followed by micro-insured loans.[6]

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[5] Note that if we allow $\varphi > \frac{R}{p}$, then farmers become indifferent between micro- and meso-insured loans.

[6] In our profit calculations, we assume that the banks bear no cost for the loans that they provide to the farmer. Even if we add a cost to the bank for these loans, the conclusions remain the same.

Next, we extend the results above by assuming that male and female farmers differ with respect to creditworthiness, φ, as previous studies (reviewed above) have found. In particular, the population of farmers is equally divided between females, denoted as *f,* and males, denoted as *m,* with the average creditworthiness of females given by $\overline{\varphi}_f$ and that of males by $\overline{\varphi}_m$ such that $\overline{\varphi}_f > \overline{\varphi}_m$.

Then, from Equations 1-3, we find that:

$$U_{kf} > U_{km} \text{ for } k \in \{U, IC, BC\} \tag{9}$$

and

$$U_{ICg} > U_{BCg} > U_{Ug} \text{ for } g \in \{f, m\} \tag{10}$$

Therefore, both female and male farmers are more likely to apply for insured loans, compared to uninsured loans. Comparing across gender, we find that female farmers are more likely to apply for insured loans than male farmers.

From the bank's perspective, from Equations 5-7, we have,

$$\prod_{BCg} > \prod_{ICg} > \prod_{Ug} \text{ for } g \in \{f, m\} \tag{11}$$

Furthermore, because $\overline{\varphi}_f > \overline{\varphi}_m$, we have,

$$\prod_{Uf} > \prod_{Um} \tag{12}$$

and

$$\left(\prod_{km} - \prod_{Um}\right) > \left(\prod_{kf} - \prod_{Uf}\right) \text{ for } k \in \{IC, BC\} \tag{13}$$

Therefore, a bank is more likely to approve loans for both females and males with insured loans, with a higher likelihood for meso-insured loans than micro-insured loans. Comparing across gender, we find that the insurance results in a greater improvement in the likelihood to approve loans for males than for females, and the magnitude of this effect is larger for meso-insured loans. In conclusion, we make the following testable propositions based on the model:

Proposition 1 – Both micro- and meso-insured loans increase the likelihood of loan application, with a greater degree of increase for micro-insured loans than meso-insured loans.

Proposition 2 – Both micro- and meso-insured loans increase the likelihood of loan approval, with a greater degree of increase for meso-insured loans than micro-insured loans.

Proposition 3 – The increase in likelihood of loan application in both micro- and meso-insured loans is higher for females than males.

Proposition 4 – While both females and males will experience a higher probability of approval for insured loans, males will experience a higher net likelihood of approval than females.

4. Experimental Design and Descriptive Statistics

4.1 Experimental design and data collection

We designed and implemented micro-level and meso-level insured loan products for maize crop with GAIP and our partner banks. We focused on maize because it is the primary crop for farmers in northern Ghana and one of the two products currently covered by GAIP. For the micro-insured loans, the FGs are the policy holders hence any payouts would go directly to them. Conversely, for meso-insured loans, the lender is the policy holder and is expected to credit the insurance payouts towards the outstanding debt of the group, fully forgiving the loan in the case of a full insurance payout. The requirements of insured loan applications remain the same as the traditional agricultural loans from the RCBs.

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. We subsidize the insurance premium as we want to measure the average treatment effect on the treated (ATT) of the insured loan products. Full subsidization allows us to ensure that there is no selection in participation based on the price of the insurance. Our approach of offering fully subsidizing loans allows us to also interpret our results as the impact of drought-based risk on credit market access.

We visited northern Ghana in November 2014 for a pilot test of our survey instrument and to establish direct working relationships with our partners, RCBs and GAIP. In addition, we met with several FGs and held focus group discussions with them. More importantly, we obtained a preliminary FG sample from the RCBs containing information on the total number of group members, gender breakdown, community location, loan size, two primary crops farmed, acreage planted, and loan status in the previous year. This sample consisted of a list of 791 groups of both existing and potential borrower FGs for the 14 participating RCBs.[7] To ensure that the study targets the FGs of the greatest interest given our budget constraints, we applied the following five criteria to select our final sample: (i) FGs that are in good standing with the bank in terms of borrowing record at the time of selection, potential groups that are

[7] Of the sixteen RCBs in northern Ghana, we partnered with fourteen: Bangmarigu, Bessfa, Bongo, Bonzali, Borimanga, Builsa, East Mamprusi, Lawra, Naara, Nandom, Sissala, Sonzele, Tizaa, and Toende.

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 concerns and budget constraints (insurance premiums are fully subsidized); and finally (v) FGs that take out a loan of less than 10,000 Ghana Cedis (GHc) so as to maintain a focus on the most low income groups.[8]

This process resulted in a sample of 258 FGs, roughly representing 2500 farmers. Female farmers make up 47% of the FGs in our sample, which is higher than the national representation of female farmers of 30%. In this sense, female farmers are overrepresented in our sample. Ninety-eight of these FGs are located in the Northern region in seven districts, 132 FGs in Upper East in nine districts, and 28 FGs in Upper West in six districts. Figure 1 presents the number of farmer groups per district in the northern regions. Table 1 further presents a breakdown of FGs in each district and region.

[Insert Figure 1 here]

[Insert Table 1 here]

To ensure a representative sample of farmers from the FGs, we randomly selected six members from each of the 258 FGs. Of these six, we picked the first three as our respondents and the remaining three as replacements in case any of the first three were unavailable for the interview. We conducted a baseline survey of a total of 779 farmers in February to March of 2015. We stratified our sample by regions and loan status where loan status indicates whether an eligible FG 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 FGs that otherwise would stay out of the credit market to request loans or FGs otherwise rejected would be approved by the banks. We then randomly assigned FGs to three roughly equal categories: (i) micro-insured loans (Treatment 1), (ii) meso-insured loans (Treatment 2), and (iii) traditional agricultural loans without drought index insurance (Control). To mitigate fairness concerns which may arise when farmers in the same group are treated differently (Giné and Yang 2009), all farmers in the treatment groups are offered the chance to apply for insured loans.

Table 2 contains the number of FGs within each region by treatment categories. We list the number of individual farmers in parentheses. At the time of the randomization, we verified that the three

[8] 1 GHc = 0.293 USD as of February 2015.

categories are not statistically different in terms of preexisting financial, agricultural, demographic, and geographical data--areas identified in the literature (Table 3).

[Insert Table 2 here]

[Insert Table 3 here]

At the end of the baseline survey, we trained a team of loan officers from each of the 14 RCBs with the help of GAIP in general descriptions of index insurance, DII, and insured loans in April 2015. Each of the loan officers was given a list of FGs in our study that corresponded to their respective bank and their assigned treatment category. The loan officers then met with each FG, described the loan product to which they were assigned (i.e., micro-insured loans for FGs under Treatment 1, meso-insured loans for FGs under Treatment 2, and traditional agricultural loans without DIIs for FGs under the Control), and invited them to apply for that loan product. The description of the loan products included a description of the three stage insurance coverage for maize, the basic features of index insurance including the presence of basis risk, the insurance payout mechanisms to the individual (bank) for Treatment 1 (Treatment 2), and informed FGs that during the first two years of the products there is no additional cost for the insured loan.[9,10] Although one can argue that this unusual face-to-face visit might in itself inspire higher loan application rates, numbers in the follow-up survey show otherwise. Means of the loan application variable, when compared to the baseline round, show that the application rates have gone down for both treatments and control groups (see Table 7).

After the invitation process, the FGs were left to their usual process of application, which they file either through their group secretaries or with the help of other parties such as MOFA extension agents. Once the FGs applied for loans, they were then approved or rejected by the RCBs following their usual appraisal criteria. Other than the risk protection afforded by the drought index insurance, no further benefit accrued to FGs or banks with insured loans. The loan application and approval criteria, interest rates, and payment schedules for the insured loans were identical to those of traditional 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. A total of eight missing respondents were replaced by randomly selected farmers of the same gender from their respective FGs. Of the eight missing, two replacements were made in the Control, four in micro-insured loan, and two in meso-insured loan categories.

[9] The three stages covered by the drought-index insurance are: germination, crop growth, and flowering.

[10] The loan officers described the insured loans to Treatment FGs 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.

4.2 Descriptive statistics

We present descriptive statistics of key variables for the baseline round (R0) and follow-up round (R1) in Table 4. Time invariant variables are presented for R0 only. We further conducted mean t-test comparisons by gender for selected variables which we present in Table 5. We discuss a selection of these variables in this subsection. We collected data on household income, agricultural income, number of agricultural plots owned, cattle, and remittances as proxies for household wealth and assets. Among these, we find that the number of plots owned is significantly higher in R1. We also collected data on risk perception, risk aversion, and mechanisms to cope with risk. For risk perception, we find that farmers perceive a slightly higher number of good seasons out of the past five seasons in R1. For risk aversion, we use a self-reporting technique via a five-point Likert scale for risk aversion from lowest to highest level of risks (Hardeweg, Menkhoff, and Waibel 2011).

[Insert Table 4 here]

Among the proxies for financial access, we gathered information on whether households have savings with the bank, outstanding debt, loan status pre-R0, and whether they applied and were approved for agricultural loans. Information on outstanding debt status is provided by the RCBs. Among those that took loans, 23 and 32% of the households have outstanding debt in R0 and R1, respectively. 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 FG secretaries and RCBs. Doing so, we find that 91% of the sample applied for loans in R0, among which 76% were approved (Table 4). 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, among which 79% were approved.

[Insert Table 5 here]

For the gender disaggregated comparison, we find that females have significantly lower agricultural income, fewer number of plots owned, less cattle, and less savings than males (Table 5), which is consistent with the literature. Similarly, females have higher risk aversion than males. For the loan application variable, we find that females have higher application rates than males in both R0 and R1. Although females are applying at a higher rate, studies have found that they usually apply for smaller loans. This is also evident in our sample, where female farmers apply for significantly smaller loan amount than male farmers. For the loan approval variable, we find that although females have a higher approval rate in R0, this pattern reverses in R1. This confirms our earlier speculation that banks see females as more creditworthy in the absence of risk reducing mechanisms.

[Insert Table 6 here]

Table 6 presents mean t-test comparisons of loan application (Panel A) and approval variables (Panel B) for all and new applicants. 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 loan application for micro-insured loans are significantly higher than the Control for R1. Similarly, from Panel B, we find that the means of loan approval variable are significantly higher for both micro- and meso-insured loans for R1.

[Insert Table 7 here]

Table 7 presents mean t-test comparisons for gender disaggregated sample. We drop the subgroup new applicants here as the sample size gets too small. From Panel A, we find that in R1, the means of loan application variable are significantly higher than the Control for both micro- and meso-insured loans for females but not males. From Panel B, we find that both micro- and meso-insured loans have significantly higher means of loan approval for females in R1. In contrast, only the meso-insured loan has a significantly higher mean of loan approval for males in R1.

5. Empirical Model and Results

5.1 Empirical Model

We use the following difference-in-differences (DID) linear probability model for our empirical analysis:

$$Y_{it} = \alpha + \gamma T1 + \mu T2 + \lambda R_t + \theta(T1 * R_t) + \beta(T2 * R_t) + \delta X_{it} + \varepsilon_{it} \qquad (14)$$

where *i* and *t* index individual and survey round, respectively. Y_{it} takes a value of one for farmers who applied for loans and zero otherwise in the loan application estimation model. Similarly, Y_{it} takes a value of one for farmers who are approved for loans and zero otherwise in the loan approval estimation model. $T1$ is one for those farmers assigned to the micro-insured loan treatment group and zero otherwise. Likewise, $T2$ is one for farmers in the meso-insured loan treatment group and zero otherwise. R_t is a round dummy which takes a value of zero for the baseline survey and one for the follow-up survey. The parameters of interest are θ and β; they respectively measure the impacts of micro- and meso-insured loans on loan application and approval. 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 DID estimates. The control variables include the number of plots owned by the respondent, age of the respondent, outstanding debt from last borrowing season, whether the respondent has savings with the RCB, the respondent's perception of total number of good seasons in the past five seasons, and the 14 bank dummies. Including the RCB dummies is important to control for bank-level heterogeneity. The additional 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). Moreover, we find that number of plots, outstanding debt, and the perception of number of good seasons in the past five seasons are significantly different across the survey rounds (Table 4).

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 a biased estimate of 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 application status of the total sample and find that number of plots, outstanding debt, respondent's age, and whether the farmers have savings with the bank are significantly different for those farmers that applied for loans and those that did not (Table 8).

[Insert Table 8 here]

Among these variables, the primary determinant of both application and approval is the FG's debt status. FGs that have outstanding debt from the previous year are less likely to apply for the next loan cycle because banks usually do not approve them. Additionally, although, the group network along with a small amount of savings serve as collateral in group lending, RCBs have information on plot ownership and may be accounting for these assets while deciding on loan approvals. The respondents' age could be a signal for creditworthiness if older members have been with the banks longer and have therefore earned their trust. Lastly, having savings with the bank is mandatory for loan application, especially for newer FGs which are required to have a savings balance of 20% of their loan application amount held with the banks.[11] Therefore, we control for these variables in our empirical models for loan application and approval.

5.2 Results and Discussion

To investigate the impact of our two treatments on credit access, we estimate several variants of our DID model, which we group in three steps. In the first step, we estimate the treatment impacts on loan application outcomes for all and new applicants. We employ three model specifications to progressively build more efficient results. Model 1 is a basic version with only the treatment variables, the round dummy, and their interaction terms. In Model 2, we add interaction terms between rounds and RCB

[11] Source: northern chapter of association of rural banks (ARB).

dummies to control for bank-level heterogeneity in loan application and approval. Finally, in Model 3, we add the covariates, X_{it}, discussed above. Models 4, 5, and 6 (new applicants) follow the specifications of Models 1, 2, and 3, respectively. In the second step, we use the same specifications to estimate the treatment impacts on loan approval for all and new applicants. In the third and final step, we re-estimate the treatment impacts on loan application and approval rates by gender. Specifically Models 1, 2, and 3 present estimations for female farmers and include no control variables (Model 1), bank dummies (Model 2), and additional covariates mentioned earlier (Model 3). Likewise, Models 4-6 follow and present estimations for male farmers. Note that we do not perform estimations for new applicants for the gender disaggregated sample as the sample size becomes too small.

5.2.1 Treatment Impacts on Loan Application for All and New Applicants

Table 9 presents DID estimates of the treatment impacts on loan application variable with standard errors clustered at the FG level. The first three columns present estimates for all applicants (Models 1-3) and the last three columns present estimates for new applicants (Models 4-6).

[Insert Table 9 here]

For the full sample, we find positive signs for the treatment impacts ranging from 8.2 to 7.1 percentage points for micro-insured loans and 5.8 to 6.0 percentage points for meso-insured loans. However, they are not statistically significant for any of the treatments. We find that in Model 3, the coefficient on savings is positive and significant, indicating that FGs with a savings account are more likely to apply for loans. This is likely due to the savings requirement for loan approval. The treatment impacts for new applicants also carry positive but insignificant signs. We conclude, based on these results that insured loans do not increase the likelihood of farmers' loan application on average. The reason for this may be because we have an application rate of 90% in the baseline period.

5.2.2 Treatment Impacts on Loan Approval for All and New Applicants

Table 10 presents the DID estimates of the treatment impacts on the loan approval variable, with FG-level clustered standard errors. We again progressively build efficient models by adding RCB-level controls in Models 2 and 5, and additional covariates in Models 3 and 6.

[Insert Table 10 here]

For all applicants, we find that positive impacts of micro-insured loans range from 8.4 to 11 percentage points, however, they are not significant (Models 1-3). For meso-insured loans, however, we find that the estimated impacts are large, positive, and statistically significant at the 5% level and range from 21 to 23 percentage points. When we move to the sample of new applicants, these results become statistically insignificant, perhaps due to the much smaller sample size (Models 4-6). In short, we find that meso-insured loans significantly increase the likelihood of a farmer's loan approval, partially corroborating our theoretical prediction in Proposition 2. While theoretically loan approval should increase with micro-insured loans, farmers get the insurance payouts in case of a drought here and banks may lack confidence that the FGs will payback. Instead, farmers could use the payout for consumption smoothing. Besides the treatment impacts, we find in Model 3 that having outstanding debt adversely impacts the likelihood of approval as expected, while the number of agricultural plots significantly increases loan approval probability.

5.2.3 Treatment Impacts by Gender

Table 11 presents the estimated treatment impacts on loan application by gender. The first three columns present estimates for female applicants (Models 1-3) and the last three columns present estimates for male applicants (Models 4-6).

[Insert Table 11 here]

While we did not find a significant impact of the treatment on loan application for the pooled sample, we find that for female applicants, micro-insured loans increase the likelihood of loan application by between 14 and 16 percentage points. These effects are statistically significant at the 10% level. The estimated impacts of meso-insured loans are positive but not significant. No significant treatment impacts are found for male farmers (Models 4-6). These results partially confirm Prediction 3 in that we find a significant increase in loan application probability for females for micro-insured loans and no significant increase for males. These results are also consistent with previous findings that the provision of a safety net during negative shocks produces higher benefits for the more risk-rationed and vulnerable population such as female-headed households (Fletschner, Anderson, and Cullen 2010; Shoji 2010). Although the theoretical model predicted that there should be an increase with meso-insured loans, we speculate that farmers may not fully trust the bank to use the insurance payouts to forgive their loans, inducing them to behave differently in reality.

Next, we present the DID estimates of the treatment impacts on the loan approval variable by gender in Table 12. The first three columns present estimates for female applicants (Models 1-3) and the last three columns present estimates for male applicants (Models 4-6).

[Insert Table 12 here]

For both male and female applicants, the estimated impacts of micro-insured loans on loan approval are positive but insignificant. For meso-insured loans, however, we find that the coefficients are significant and range from 20 to 22 percentage points for females and 24 to 25 percentage points for males. Furthermore, the estimated impact for males (per Model 6) is significantly larger than the estimated impact for females (Model 3).[12] These results confirm our Proposition 4 in that reducing the risk of defaults with meso-insured loans benefits male farmers more so than female farmers who are seen as more creditworthy (Sharma and Zeller 1997; D'Espallier, Guérin, and Mersland 2011). Again, the insignificant impacts for micro-insured loans on approval could be caused by banks not trusting that farmers will use the payouts to repay their loans.

6 Conclusion and Policy Implications

Sixty per cent of the projected increase in food demand over the next fifteen years is expected to originate from SSA countries (World Bank 2016). This is a critical issue since SSA countries have the highest prevalence of food insecurity and have experienced decreasing agricultural outputs over the last decade (Suri 2011). Therefore, barriers to technology adoption, such as limited credit access and systemic production risk need immediate attention. In this regard, we devised a simple theoretical model to motivate our empirical work on the impact of insured loans on credit access. We then conducted an RCT of drought index insured loans with two distinct treatments. In Treatment 1, loans offered to the farmer groups are coupled with index insurance, with the contract assigned to the farmer groups. In Treatment 2, 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.

Using a difference-in-differences linear probability model, we find limited evidence that insured loans have a significant impact on loan application; specifically, micro-insured loans increase the likelihood of loan application among female farmers. These findings contrast with our prediction to some extent as we expected the loan application probabilities to increase across the board. We speculate that the positive but mostly insignificant results could be because our sample is largely drawn from a pool of existing bank clients with a 90% average application rate in the baseline period. Thus, if insured loans are broadly made available to smallholder farmers, they could significantly boost loan application rates. A major finding of the paper is that insuring agricultural loans in a way that guarantees full loan repayment during a drought

[12] We calculate the confidence interval of treatment impact for female farmers from Model 3, Table 12, by choosing a 95% confidence level, beta = 0.218, std. = 0.128, and sample size = 633. We obtain the upper confidence boundary as .227, which is lower than the lower boundary of impact on male farmers with a beta of 0.249 at 95% confidence level, std. = 0.104, and sample size = 698.

allows lenders to expand credit access to smallholders. This is evidenced by the fact that the meso-insured loan product spurs a quantitatively large increase in the likelihood of loan approval for both female and male farmers, although the impact is higher for male farmers. Taken together, our findings indicate that reducing systemic risk for borrowers and lenders can serve as a springboard to expanded credit access and associated efficiency-enhancing technology adoption that is desperately needed in SSA countries.

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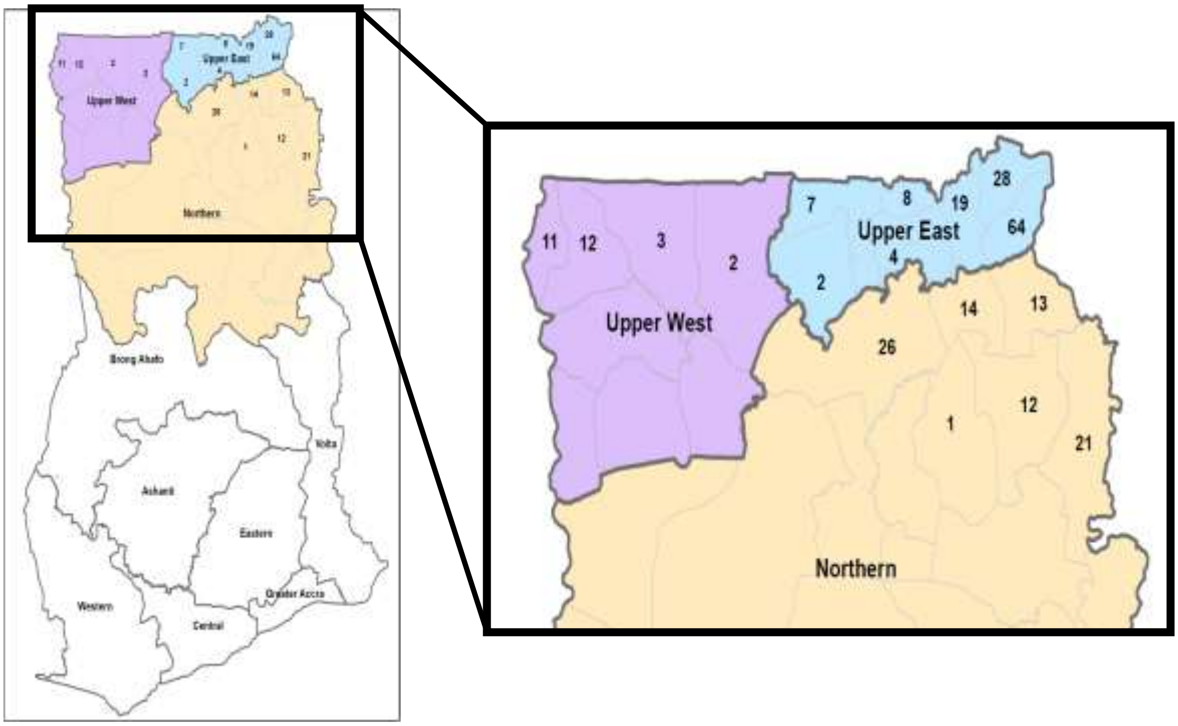
FIGURES AND TABLES

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



The figure displays the number of farmer groups (FGs) for each district represented in our sample. The district names are omitted for clarity but listed along with FGs in each district in Table 1.

Table 1: Farmer Groups by Regions and Districts

Districts	No. of farmer groups
Northern	*98*
Bonkpirigu Yongyong	13
East Mamprusi	14
West Mamprusi	26
Gushegu	12
Saboba -Chereponi	32
Karaga	1
Upper East	*132*
Bongo	8
Builsa	2
Bawku Municipal	15
Bawku West	19
Binduri	13
Bolgatanga Municipal	4
Garu Tempane	64
Kassena Nankana West	2
Kassena Nankana East	5
Upper West	*28*
Jirapa - Lambussie	12
Lawra-Nandom	11
Sissala East	2
Sissala West	3
Total	258

Table 2: 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 3: Checking the balance of randomization across Control, Treatment 1, and Treatment 2 categories via One-way analysis of variance (ANOVA)

	Category	Mean	Std.	P-Value
Maize quantity (bags)				0.19
	Control	11	22.34	
	Treatment 1	12	46.07	
	Treatment 2	8	9.81	
Fertilizer quantity (Packet)				0.94
	Control	.86	.35	
	Treatment 1	.86	.35	
	Treatment 2	.86	.34	
Hybrid binary (1=use)				0.65
	Control	.14	.35	
	Treatment 1	.15	.36	
	Treatment 2	.13	.34	
Number of loans taken				.84
	Control	.66	.63	
	Treatment 1	.63	.62	
	Treatment 2	.64	.62	
Loan Binary (1=taken)				0.88
	Control	.60	.49	
	Treatment 1	.58	.49	
	Treatment 2	.59	.49	
Loan Amount (GHc)				.37
	Control	372	194	
	Treatment 1	388	396	
	Treatment 2	342	182	
Default Binary (1=defaulted)				.84
	Control	.16	.37	
	Treatment 1	.15	.36	
	Treatment 2	.17	.38	
Total Income (GHc)				.45
	Control	2098	1757	
	Treatment 1	1994	1574	
	Treatment 2	1881	1560	
Agricultural Income (GHc)				0.74
	Control	1486	990	
	Treatment 1	1477	917	
	Treatment 2	1425	907	
Time taken to input market (hours)				0.58
	Control	0.06	.05	
	Treatment 1	0.06	.04	
	Treatment 2	0.06	.07	
Aggregator binary (1=sell via aggregator)				.67
	Control	.07	.25	
	Treatment 1	.05	.22	

Treatment 2	.06	.23	
Good season (1=2014 was a good season)			.93
Control	.40	.49	
Treatment 1	.42	.49	
Treatment 2	.40	.49	
Risk aversion (Likert Scale 1-5)			.67
Control	2.1	1.11	
Treatment 1	2.1	.98	
Treatment 2	2.2	1.09	
Maize planted land (Acres)			.33
Control	2.9	3.11	
Treatment 1	2.9	4.74	
Treatment 2	2.5	2.44	
Number of household members			.31
Control	8.6	3.17	
Treatment 1	8.4	3.34	
Treatment 2	8.2	3.40	
Medical emergency (No. of people)			.50
Control	.49	.50	
Treatment 1	.49	.50	
Treatment 2	.43	.50	
Borrow cash/in-kind			.65
Control	.95	.21	
Treatment 1	.92	.27	
Treatment 2	.95	.23	
Death			.86
Control	.75	.43	
Treatment 1	.72	.45	
Treatment 2	.74	.44	
Crop loss			.32
Control	.22	.42	
Treatment 1	.31	.47	
Treatment 2	.20	.41	
Cash loan (1=prefer loan in cash)			.44
Control	.56	.50	
Treatment 1	.51	.50	
Treatment 2	.53	.50	
Price of maize (GHc/per bag)			.45
Control	144	191	
Treatment 1	159	215	
Treatment 2	137	189	
Proportion of plots planted with maize			.33
Control	.42	.22	
Treatment 1	.42	.24	
Treatment 2	.45	.40	
Remittances (GHc)			.25
Control	117	218	
Treatment 1	102	215	

	Treatment 2	87	180	
District				0.5
	Control	11	6.66	
	Treatment 1	12	7.23	
	Treatment 2	12	6.80	

We performed the Kruskal–Wallis test by ranks, a non-parametric method for testing whether samples originate from the same distribution, and found similar results.

Table 4: Descriptive statistics of key variables over round

	Baseline (Round 0)		Follow-up (Round 1)		
Variable	Mean	Std.	Mean	Std.	P-value
Loan application	.91	.28	.80	.40	.00
Loan approval	.76	.43	.79	.41	.19
Agricultural income	1378	906	1370	946	.86
Total income	2323	1493	2269	1536	.48
No. of plots owned	3	1.05	3.9	2.30	0.00
Cattle	3.5	4.95	4.2	14.3	.22
Remittances (GHc)	110	210	115	218	.59
Saving (GHc)	356	477	334	459	.36
Debt (1=outstanding debt)	.20	.40	.32	.47	0.00
Respondent age	45	13	46	13	.20
No. of HH members	9.7	5.9	9.4	4.7	.25
No. of help in case of draught	2.0	3.3	1.81	2.2	.16
No. of last 5 good seasons	2.36	.92	2.48	.82	.01
Time invariant variables	Sample Proportion				
Risk aversion					
1. Very willing to take risk	0.32				
2. Willing to take risk	0.39				
3. Indifferent to taking risk	0.12				
4. Not willing to take risk	0.15				
5. Not at all willing to take risk	0.01				
Borrowing status in year 2014					
Non-Borrower	0.27				
Borrower	0.73				
Respondent gender					
Male	0.53				
Female	0.47				
Respondent education					
No education	.79				
Primary education	.05				
Middle school	.06				
High School	.07				
College or more	.02				

Table 5: Pairwise Mean Comparisons for Males and Females by Round

	Round 0			Round 1		
	Females	Males	Difference	Females	Males	Difference
Credit access parameters						
Loan application	.94	.90	**	.81	.78	
Loan approval	.77	.75		.76	.81	
Wealth parameters						
Agric. Inc. (GHc)	1209	1525	***	1250	1473	***
Number of Plots	2.97	3.03		3.70	4.08	**
Cattle	2.85	4.12	***	3.15	5.10	*
Remittance (GHc)	109	110		105	125	
Amt. Saved (GHc)	318	389	**	303	361	*
Risk Parameters						
Draught Help	2.1	1.95		1.9	1.78	
Good Season 5	2.3	2.4		2.4	2.5	**
Risk Aversion	2.19	2.08	**	---	---	

*** p<0.01, ** p<0.05, * p<0.1. Amount saved is the savings with the bank; Draught help is the number of people the farmer can get help from in case of draught; Good season 5 represents how many of the past 5 seasons the farmer thinks was a good season; and Risk aversion is a 5-point Likert Scale measured during baseline.

Table 6: Pairwise Mean Comparisons for All and New Applicants

Variables	Control	Treatment1		Treatment2	
PANEL A – LOAN APPLICATION PROBABILITIES					
Loan Application All Round 0	0.9189	0.9310		0.8957	
Loan Application All Round 1	0.7567	0.8506	***	0.7915	
Loan Application New Round 0	0.8209	0.8333		0.7826	
Loan Application New Round 1	0.6418	0.8333	***	0.7826	*
PANEL B - LOAN APPROVAL PROBABILITIES					
Loan Approval All Round 0	0.7689	0.7901		0.7241	
Loan Approval All Round 1	0.6888	0.8243	***	0.8536	***
Loan Approval New Round 0	0.0545	0.2	**	0	
Loan Approval New Round 1	0.4884	0.7	**	0.5	

*** p<0.01, ** p<0.05, * p<0.1.

Table 7: Pairwise Mean Comparisons for Female and Male Applicants

	Control	Treatment1		Treatment2	
PANEL A – LOAN APPLICATTION PROBABILITIES					
Female Applicants Round 0	0.9459	0.9440		0.9212	
Female Applicants Round 1	0.7207	0.8800	***	0.8189	*
Male Applicants Round 0	0.8986	0.9191		0.8712	
Male Applicants Round 0	0.8235	0.8235		0.7651	
PANEL B – LOAN APPROVAL PROBABILITIES					
Female Approvals Round 0	0. 7523	0. 8135		0. 7436	
Female Approvals Round 1	0. 6125	0. 8364	***	0. 8077	***
Male Approvals Round 0	0. 7819	0. 7680		0. 7043	
Male Approvals Round 1	0.7414	0.8125		0.9010	***

*** p<0.01, ** p<0.05, * p<0.1.

Table 8: Pairwise Mean T-test Comparisons for key variables by application status for the whole sample

	Apply	Did not Apply	Difference
Agric. Inc. (GHc)	1377	1351	
No. of Plots	3.3	3.9	***
Cattle	4.0	3.8	
Remittances (GHc)	93	115	
Saving binary	.65	.75	***
Respondent age	44	46	**
Draught Help	1.9	1.9	
Good Season 5	2.3	2.4	
Risk Aversion	2.2	2.1	
Debt	.36	.24	***

*** p<0.01, ** p<0.05, * p<0.1. Amount saved is the savings with the bank; Draught help is the number of people the farmer can get help from in case of draught; Good season 5 represents how many of the past 5 seasons the farmer thinks was a good season; and Risk aversion is a 5-point Likert Scale measured during baseline.

Table 9: Treatments Impacts on Loan Application Probability for All and New Applicants

	All Applicants			New Applicants		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treatment 1	0.012	0.012	0.011	0.012	0.012	-0.020
	(0.040)	(0.040)	(0.042)	(0.113)	(0.114)	(0.124)
Treatment 2	-0.023	-0.023	-0.027	-0.038	-0.038	-0.060
	(0.044)	(0.044)	(0.046)	(0.120)	(0.121)	(0.126)
Round	-0.162***	-0.119	-0.108	-0.179	0.043	0.080
	(0.052)	(0.092)	(0.092)	(0.122)	(0.118)	(0.119)
Treatment1*Round	0.082	0.076	0.071	0.179	0.180	0.187
	(0.066)	(0.066)	(0.066)	(0.149)	(0.140)	(0.139)
Treatment 2*Round	0.058	0.060	0.060	0.179	0.166	0.169
	(0.071)	(0.071)	(0.071)	(0.175)	(0.154)	(0.150)
Outstanding Debt			-0.036			-0.068
			(0.046)			(0.120)
Saving			0.066***			0.125**
			(0.023)			(0.051)
No. of plots			-0.006			-0.013
			(0.007)			(0.013)
Respondent age			0.002***			0.002
			(0.001)			(0.002)
Good season 5			0.000			0.029
			(0.010)			(0.019)
Constant	0.919***	0.919***	0.799***	0.821***	0.821***	0.645***
	(0.029)	(0.030)	(0.065)	(0.082)	(0.083)	(0.159)
Bank Dummies	No	Yes	Yes	No	Yes	Yes
Observations	1,558	1,558	1,553	416	416	415
R-squared	0.034	0.099	0.113	0.025	0.186	0.215

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks have been included in the dummy. Outstanding debt is a variable that is defined as having outstanding payback post the timeline for repayment; saving is a binary variable that takes 1 if the farmer groups have savings with the bank and 0 if not; number of plots is the number owned by the farmers; and good season 5 is the number of good seasons in the past 5 seasons.

Table 10: Treatments Impacts on Loan Approval Probability for All and New Applicants

	All Applicants			New Applicants		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treatment 1	0.021	0.021	0.004	0.145	0.145	0.124
	(0.065)	(0.066)	(0.066)	(0.105)	(0.107)	(0.098)
Treatment 2	-0.045	-0.045	-0.063	-0.055	-0.055	-0.063
	(0.070)	(0.070)	(0.070)	(0.054)	(0.055)	(0.052)
Round	-0.080	-0.033	-0.088	0.434***	-0.129	-0.157
	(0.069)	(0.116)	(0.109)	(0.146)	(0.092)	(0.096)
Treatment1*Round	0.114	0.084	0.103	0.066	-0.042	-0.028
	(0.088)	(0.088)	(0.090)	(0.182)	(0.155)	(0.155)
Treatment 2*Round	0.210**	0.221**	0.230***	0.066	0.127	0.132
	(0.088)	(0.086)	(0.088)	(0.189)	(0.084)	(0.092)
Outstanding Debt			-0.127**			-0.053
			(0.057)			(0.081)
Saving			-0.009			-0.021
			(0.029)			(0.056)
No. of plots			0.020***			-0.005
			(0.006)			(0.012)
Respondent age			-0.000			0.001
			(0.001)			(0.001)
Good season 5			0.008			0.020
			(0.013)			(0.026)
Constant	0.769***	0.769***	0.754***	0.055	0.055	0.035
	(0.048)	(0.048)	(0.077)	(0.054)	(0.055)	(0.116)
Bank Dummies	No	Yes	Yes	No	Yes	Yes
Observations	1,336	1,336	1,331	326	326	325
R-squared	0.017	0.110	0.128	0.308	0.693	0.697

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks have been included in the dummy. Outstanding debt is a variable that is defined as having outstanding payback post the timeline for repayment; saving is a binary variable that takes 1 if the farmer groups have savings with the bank and 0 if not; number of plots is the number owned by the farmers; and good season 5 is the number of good seasons in the past 5 seasons.

Table 11: Treatments Impacts on Loan Application Probability for Female and Male Applicants

	Female Applicants			Male Applicants		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treatment 1	-0.002	-0.002	-0.006	0.020	0.020	0.023
	(0.045)	(0.045)	(0.045)	(0.055)	(0.056)	(0.057)
Treatment 2	-0.025	-0.025	-0.031	-0.027	-0.027	-0.030
	(0.046)	(0.047)	(0.048)	(0.060)	(0.061)	(0.062)
Round	-0.225***	-0.120	-0.112	-0.115*	-0.137	-0.126
	(0.074)	(0.088)	(0.085)	(0.060)	(0.135)	(0.137)
Treatment1*Round	0.161*	0.152*	0.141*	0.019	0.014	0.010
	(0.086)	(0.086)	(0.086)	(0.079)	(0.080)	(0.081)
Treatment 2*Round	0.123	0.116	0.116	0.009	0.021	0.021
	(0.092)	(0.091)	(0.091)	(0.091)	(0.089)	(0.089)
Outstanding Debt			-0.043			-0.038
			(0.050)			(0.066)
Saving			0.068**			0.063**
			(0.030)			(0.031)
No. of plots			-0.005			-0.004
			(0.009)			(0.008)
Respondent age			0.002*			0.002**
			(0.001)			(0.001)
Good season 5			0.012			-0.009
			(0.015)			(0.012)
Constant	0.946***	0.946***	0.810***	0.899***	0.899***	0.797***
	(0.033)	(0.033)	(0.080)	(0.041)	(0.041)	(0.084)
Bank Dummies	No	Yes	Yes	No	Yes	Yes
Observations	726	726	725	832	832	828
R-squared	0.056	0.165	0.181	0.025	0.084	0.097

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks have been included in the dummy. Outstanding debt is a variable that is defined as having outstanding payback post the timeline for repayment; saving is a binary variable that takes 1 if the farmer groups have savings with the bank and 0 if not; number of plots is the number owned by the farmers; and good season 5 is the number of good seasons in the past 5 seasons.

Table 12: Treatments Impacts on Loan Approval Probability for Female and Male Applicants

	Female Applicants			Male Applicants		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Treatment 1	0.061	0.061	0.040	-0.014	-0.014	-0.022
	(0.086)	(0.087)	(0.085)	(0.081)	(0.082)	(0.083)
Treatment 2	-0.009	-0.009	-0.035	-0.078	-0.078	-0.091
	(0.093)	(0.094)	(0.091)	(0.087)	(0.088)	(0.089)
Round	-0.140	-0.134	-0.198	-0.041	0.091	0.043
	(0.103)	(0.164)	(0.155)	(0.078)	(0.084)	(0.086)
Treatment1*Round	0.163	0.111	0.123	0.085	0.070	0.081
	(0.125)	(0.129)	(0.133)	(0.102)	(0.103)	(0.106)
Treatment 2*Round	0.204*	0.203*	0.218*	0.237**	0.243**	0.249**
	(0.122)	(0.126)	(0.128)	(0.107)	(0.101)	(0.104)
Outstanding Debt			-0.126*			-0.120
			(0.071)			(0.074)
Saving			-0.023			0.004
			(0.037)			(0.039)
No. of plots			0.025**			0.016**
			(0.011)			(0.008)
Respondent age			0.000			-0.001
			(0.001)			(0.001)
Good season 5			0.032*			-0.021
			(0.019)			(0.017)
Constant	0.752***	0.752***	0.647***	0.782***	0.782***	0.850***
	(0.067)	(0.068)	(0.120)	(0.056)	(0.056)	(0.087)
Bank Dummies	No	Yes	Yes	No	Yes	Yes
Observations	634	634	633	702	702	698
R-squared	0.026	0.145	0.166	0.020	0.121	0.138

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks have been included in the dummy. Outstanding debt is a variable that is defined as having outstanding payback post the timeline for repayment; saving is a binary variable that takes 1 if the farmer groups have savings with the bank and 0 if not; number of plots is the number owned by the farmers; and good season 5 is the number of good seasons in the past 5 seasons.

Appendix: Theory Calculations

At actuarially priced premium, we have

$$(1+r)\pi = (1-p)R^I \Rightarrow (1+r)\pi = (1-p)(1+r)(K+\pi)$$

$$\Rightarrow \pi = \frac{1-p}{p}K$$

Then, since $R = (1+r)K$ and $\pi = \frac{1-p}{p}K$, we have:

$$(1+r)\pi = (1-p)R^I \Rightarrow \frac{R}{K}\frac{1-p}{p}K = (1-p)R^I$$

$$\Rightarrow R^I = \frac{R}{p}$$

When we assume, $p = \frac{1}{2}$, $R^I = 2R$. Therefore, under micro-insured loan, if the farmer decides to repay, her expected utility becomes:

$$U_{IC} = \frac{1}{2}u(Y_H - 2R + \varphi) + \frac{1}{2}u(Y_L + \varphi) \tag{A.1}$$

where $Y_H > 2R$ and the farmer always repays in a good state so that she remains creditworthy; $Y_L < R$ so a farmer is unable to repay without insurance in a drought state. Instead, if the farmer decides to not repay, her expected utility becomes:

$$U_{IC} = \frac{1}{2}u(Y_H - 2R + \varphi) + \frac{1}{2}u(Y_L + 2R) \tag{A.2}$$

Since A.2 > A.1, we conclude that the farmer is better off not repaying and instead consumes the insurance payout in a drought state. Next, under meso-insured loan, the bank gets the payout and the farmer does not have a choice to repay or not. Therefore, the expected utility of the farmer from the meso-insured loan is:

$$U_{BC} = \frac{1}{2}u(Y_H - 2R + \varphi) + \frac{1}{2}u(Y_L + \varphi) \tag{A.3}$$

Therefore, comparing the farmer's expected utility in insured and uninsured states, we can deduce:

$$U_{IC} > U_{BC} > U_U \tag{A.4}$$

When we assume that females are more creditworthy than males, then it naturally follows that:

$$U_{kf} > U_{km} \text{ for } k \in \{U, IC, BC\} \tag{A.5}$$

and

$$U_{ICg} > U_{BCg} > U_{Ug} \text{ for } g \in \{f, m\} \tag{A.6}$$

Next, we calculate expected profits for the bank. Normalizing the number of potential borrowers to 1, the expected profit from uninsured loans, $\prod_U$, is given by:

$$\prod\nolimits_U = p^*(\varphi)R \tag{A.7}$$

The expected profit from micro-insured loans is given by:

$$\prod\nolimits_{IC} = p^*(\varphi)R + (1 - p^*(\varphi))qR \tag{A.8}$$

and expected profit from the meso-insured loans is given by:

$$\prod\nolimits_{BC} = R \tag{A.9}$$

Normalizing the number of female and male borrowers to be one and equal in proportion, expected profit from an uninsured loan is given by:

$$\prod_{Ug} = p^{*}\left(\varphi_g\right) R \text{ for } g \in \{f, m\} \tag{A.10}$$

Similarly, the expected profit from micro-insured loan, for females, is given by:

$$\prod_{ICf} - \prod_{Uf} = \left(1 - p^{*}\left(\varphi_f\right)\right) qR \tag{A.11}$$

and for males is given by:

$$\prod_{ICm} - \prod_{Um} = \left(1 - p^{*}(\varphi_m)\right) qR \tag{A.12}$$

Since $\overline{\varphi}_f > \overline{\varphi}_m$, $A.12 > A.11$.

Next, the expected profit from meso-insured loan, for females, is given by:

$$\prod_{BCf} - \prod_{Uf} = \left(1 - p^{*}\left(\varphi_f\right)\right) R \tag{A.13}$$

and for males, is given by:

$$\prod_{BCm} - \prod_{Um} = \left(1 - p^{*}(\varphi_m)\right) R \tag{A.14}$$

And since $\overline{\varphi}_f > \overline{\varphi}_m$, $A.14 > A.13$.

Therefore, with insurance, banks will be more likely to approve male farmers with meso-insured loans, followed by females with meso-insured loans, followed by male farmers with micro-insured loans and female farmers with micro-insured loans.