You are Approved! Insured Loans Improve Credit Access and Technology Adoption of Ghanaian Farmers.

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Abstract:

Increasing agricultural efficiency via technology adoption is 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 on the demand side, coupling loans with micro-insurance increases the likelihood of loan application for female farmers, potentially because of the payouts being directly made to them and a lack of trust in the bank. In contrast, coupling loans with meso-insurance increases the likelihood of loan application for those farmers who place the highest trust in the bank. On the supply side, coupling loans with meso-insurance increases the likelihood of loan approval, 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.

Acknowledegment: 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.

JEL Codes: Q14, D90

#882

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Abstract

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

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, lower trust, and higher risk aversion (Buchan, Croson, and Solnick 2008; Fletschner, Anderson, and Cullen 2010; Gladwin 1992; 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 trustworthy than women (Buchan, Croson, and Solnick 2008; Croson and Buchan 1999). Furthermore, men are perceived 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 (Cai et al. 2014; 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 less trustworthy and riskier due to higher defaults. Likewise, the insurance protection afforded to smallholders in case of a systemic event may encourage the less trusting and 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 from both the demand and supply sides, and none that explores their heterogeneity with a gender focus.

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 there is heterogeneity in these impacts, especially for female farmers on the demand side (due to lower trusting and higher risk-rationing of females) and male farmers on the supply side (due to banks' perception of males as less creditworthy and trustworthy).

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 four major findings. First, for the total sample, we find that there is no impact of insured loans on farmers' loan application probabilities. This may be 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, when we disaggregate the sample to examine the heterogeneous treatment impacts on loan application, we find that female farmers are more likely to apply for micro-insured loans by 15 percentage points. We speculate that this is because female farmers are less likely to trust the bank with the insurance payouts in a drought state. Third, we find that banks are more likely to approve loans for farmers by 24 percentage points with meso-insured loans. Finally, we find that the loan approval probability for male farmers significantly increases by 27 percentage points with meso-insured loans, but marginally insignificantly for female farmers by 22 percentage points.[1] Overall, our findings suggest that index insured loan products can simultaneously reduce both supply- and demand-side credit constraints, thereby increasing credit access and technology adoption in areas with predominantly smallholder farmers.[2] Furthermore, mechanisms that build trust between farmers and financial institutions can be beneficial to reduce credit constraints.

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).

[1] The p-value for the meso-insured loans coefficient for loan approval is 0.102 in the model with bank dummies, but is 0.06 for a model with all covariates but the bank dummies.

[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.

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 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

[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.

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 replace the illiquid collateral in their model with a liquid collateral value C which can be defined as the value of the savings the farmers have with the bank. We also introduce a default penalty $\varphi \in [0, \infty)$, which is the discounted present value of future consumption afforded by being a creditworthy borrower. Second, we explore separate impacts of micro- versus meso-level insured loans on credit access. Third, we consider these impacts from the lender's perspective in addition to the borrower's. Finally, we propose heterogeneous treatment impacts of insured loans from supply and demand sides, with a special focus on gender by varying model parameters.

3.1 Model Assumptions for Demand of Credit

Assume a representative subsistence farmer who plants a crop using either a safe traditional technology (traditional seeds) or a high return but risky improved technology (improved seeds). The traditional seeds yield Y_T with certainty. The improved technology yields Y_H with probability p and Y_L with probability $1-p$ and $Y_T < pY_H + (1-p)Y_L$.[4] Additionally, assume that the crop cycle faces two agro-ecological states, good rain h and drought l, with a good rain probability of q. Let ρ be the correlation between rainfall and yields. Then, following Giné and Yang (2009), we can write the join probabilities of yields and rainfall as $\mathrm{P}(Y_H, h) = pq + \rho\sqrt{p(1-p)q(1-q)}$, $\mathrm{P}(Y_H, l) = p(1-q) - \rho\sqrt{p(1-p)q(1-q)}$, $\mathrm{P}(Y_L, h) = (1-p)q - \rho\sqrt{p(1-p)q(1-q)}$ and $\mathrm{P}(Y_L, l) = (1-p)(1-q) + \rho\sqrt{p(1-p)q(1-q)}$. 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. The farmer also faces a small application cost κ. We assume $Y_H > R > Y_L$ and therefore high yields are required for loan repayment and low yields result in default. Consequently, low yields result in the loss of collateral savings C, and the imposition of the default penalty φ. To ensure non-negative utilities, we further assume that every farmer has an asset parameter ω that cannot be seized by the bank.

The farmer's utility is simply a function of consumption. If the farmer plants with traditional technology, her consumption is Y_T and therefore her utility $U_T = u(Y_T)$. In contrast, if she decides to plant with improved technology, her consumption is given by:

[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.

$$C_j = \begin{cases} \omega + Y_H + \mathrm{C} - R - \kappa & j = h, good\ rainfall\ state \\ \omega + Y_L - \varphi - \kappa & j = l, drought\ state \end{cases} \quad (1)$$

Therefore, the farmer's expected utility from adopting the improved technology with an uninsured loan, U_U, can be expressed as:

$$U_U = pu(\omega + Y_H + \mathrm{C} - R - \kappa) + (1-p)u(\omega + Y_L - \varphi - \kappa) \quad (2)$$

Suppose that banks offer a bundle of credit with rainfall insurance, i.e., an insured loan such that in a drought state, the insurance pays out the loan principal and interest, which includes the cost of hybrid seeds K and the insurance 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 $(1+r)\pi = (1-q)R^I$ and hence, $\pi = \frac{1-q}{q}K$. 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 $R^I = \frac{R}{q}$ (see Appendix for derivation). To ensure repayment in the high outcome state and inability to repay in the low outcome as earlier, we assume $Y_H > R^I > Y_L$.

Suppose the banks offer two types of insured loan contracts, one where payouts are given to the farmer (micro-insured loans) and another where payouts are given to banks (meso-insured loans) such that the bank uses these payouts to fully forgive the loan in case of a drought. With the micro-insured loans, the farmer gets a payout in a drought state and has the choice to either repay or not. We assume that some proportion of the population of farmers will repay the loan with the insurance payout and the rest will strategically default and keep the insurance payout. To incorporate this into our representative farmer's behavior, we assume that the farmer believes that the bank places a probability λ of strategic default and $1 - \lambda$ of repayment on her. If the farmer repays, her consumption in a drought state is $\omega + Y_L + \mathrm{C} - \kappa$ but if she does not, her consumption is $\omega + Y_L + \frac{R}{q} - \varphi - \kappa$. Therefore, her expected utility from a micro-insured loan, U_{MI}, can be expressed as:

$$\begin{aligned} U_{MI} = {} & P(Y_H, h)u\left(\omega + Y_H + \mathrm{C} - \frac{R}{q} - \kappa\right) + P(Y_H, l)u(\omega + Y_H + \mathrm{C} - \kappa) \\ & + [\lambda\left(P(Y_L, l)u(\omega + Y_L + \frac{R}{q} - \varphi - \kappa)\right) \\ & + (1-\lambda)(P(Y_L, l)u(\omega + Y_L + \mathrm{C} - \kappa))] + P(Y_L, h)u(\omega + Y_L - \varphi - \kappa) \end{aligned} \quad (3)$$

With a meso-insured loan, the bank gets a payout in a drought state and uses the payout to forgive the outstanding debt of the farmer. However, as this is a model of farmer demand, we introduce an element of farmer trust in the bank to use the insurance for the stated purpose. We specify that the representative farmer believes that there is a probability of $\tau \in [0,1]$ that the bank will use the insurance to fully forgive her loan. Thus, the expected utility of the farmer from a meso-insured loan, U_{ME}, can be expressed as:

$$U_{ME} = P(Y_H, h)u\left(\omega + Y_H + C - \frac{R}{q} - \kappa\right) + P(Y_H, l)u(\omega + Y_H + C - \kappa) + [\tau(P(Y_L, l)u(\omega + Y_L + C - \kappa)) + (1-\tau)P(Y_L, l)u(\omega + Y_L - \varphi - \kappa)] + P(Y_L, h)u(\omega + Y_L - \varphi - \kappa) \tag{4}$$

3.2 Model Simulations for Credit Demand

In this subsection, we simulate our model to derive predictions about the application behavior of farmers. These plots are basically indifference curves (ICs) between planting with traditional (i.e. no loan) and improved (i.e. loan) states. To model the cutoff or indifference between applying and not applying for each loan, we assume that the banks approve farmers' loans with probabilities P_{ME}, P_{MI} and P_U in meso-insured, micro-insured, and uninsured states, respectively, such that $P_{ME} \geq P_{MI} \geq P_U$. If the loan application is approved, the farmer will receive the loan as described in the section above. If the loan application is denied, she will be forced to use the traditional technology but still incur the cost of application.

The IC between no application and uninsured loan application can be defined as:

$$u(\omega + Y_T + C) = P_U[pu(\omega + Y_H + C - R - \kappa) + (1-p)u(\omega + Y_L - \varphi - \kappa)] + (1 - P_U)u(\omega + Y_T + C - \kappa) \tag{5}$$

Similarly, the IC between no application and micro-insured loan application can be defined as:

$$u(\omega + Y_T + C) = P_{MI}[P(Y_H, h)u\left(\omega + Y_H + C - \frac{R}{q} - \kappa\right) + P(Y_H, l)u(\omega + Y_H + C - \kappa) + [\lambda\left(P(Y_L, l)u(\omega + Y_L + \frac{R}{q} - \varphi - \kappa)\right) + (1-\lambda)(P(Y_L, l)u(\omega + Y_L + C - \kappa))] + P(Y_L, h)u(\omega + Y_L - \varphi - \kappa)] + (1 - P_{MI})u(\omega + Y_T + C - \kappa) \tag{6}$$

And finally, the IC between no application and meso-insured loan application can be defined as:

$$u(\omega + Y_T + \mathrm{C}) = P_{ME}[(Y_H, h)u\left(\omega + Y_H + \mathrm{C} - \frac{R}{q} - \kappa\right) + P(Y_H, l)u(\omega + Y_H + \mathrm{C} - \kappa) \qquad (7)$$
$$+ [\tau(P(Y_L, l)u(\omega + Y_L + \mathrm{C} - \kappa)) + (1-\tau)P(Y_L, l)u(\omega + Y_L - \varphi - \kappa)]$$
$$+ P(Y_L, h)u(\omega + Y_L - \varphi - \kappa)] + (1 - P_{ME})u(\omega + Y_T + \mathrm{C} - \kappa)$$

In order to draw the ICs, we plot a combination of the constant relative risk aversion (CRRA) coefficient and drought state yields Y_L such that the farmer is indifferent between applying for a loan to produce with improved technology and producing with the traditional crop yields. Furthermore, to examine how predictions change over different parameter specifications, we divide our simulations into five cases. We provide a list of simulation parameters, their definitions, and values in Table 1. For example, we follow Giné and Yang (2009) and assume the probability of yields with improved technology p and rainfall states q to be 0.5. Additionally, we assume a high correlation between these probabilities such that $\rho = 0.9$, high yield $Y_H = 15$ and traditional yield $Y_T = 5$. Furthermore, we assume a collateral value of $\mathrm{C} = 0.2$ and approval rates of $P_{ME} = 0.9 \geq P_{MI} = 0.8 \geq P_U = 0.7$.

In Table 2, we provide the changes in specifications of key parameters that we believe would drive the farmer application behavior (Panel A). Beyond graphically representing the five IC cases, we also generate simulated application rates for each loan type and case (Panel B). To derive these application rates, we assume a normal distribution of CRRA coefficient values within our population; evaluate equations 5-7 for 100,000 randomly drawn CRRA values; and find the proportion of these evaluations for which applying for the loan results in a higher utility. We calibrated the parameters of the normal distribution to generate application rates for the uninsured loan to roughly match the expected application rate for our target population prior to our study.[5] By this we hope to gain a rough expectation regarding the impact of the insured loans on application rates. We discuss the parameter specifications and the corresponding application rate simulation prediction for each case in turn below.

[Insert Table 1]

[Insert Table 2]

Figure 1 shows the ICs between applying and not applying for the loan where the region northwest of the IC is the area of CRRA coefficients for which individuals will choose to not apply. Micro (the red curve) is the IC between applying for the micro-insured loan or not. Meso (the green curve) is the

[5] However, in our RCT sample had a much higher application rate in the baseline than our expectation for the calibration, with an average of over 90%. In this sense, the predictions from impact of insured loans on application rates calibration can be seen an overestimation.

indifference line between applying for the meso-insured loan or not. Uninsured (the blue curve) is the indifference line between applying for the uninsured loan or not. In general, micro- and meso-insured loans allow farmers with a high risk aversion to apply for a loan. As the drought yield state output gets higher, farmers with even higher risk aversions are willing to apply for loans, effectively increasing demand for the loans.

[Insert Figure 1]

Case 1: We call this the naïve case because we assume that everyone trusts the bank fully to forgive their loans in case of a bank payout and they will strategically default in case of a payout made directly to them, i.e. $\tau = 1$ and $\lambda = 1$. Then, comparing the micro- and meso-insured loans, we find that the micro-insured loans will attract farmers with high risk aversions. The predicted application rates are 99, 84 and 68% for micro-insured, meso-insured and uninsured loans, respectively. The strong demand for the micro-insured loan is likely driven by the large utility increase in the drought state where farmers may strategically default.

Case 2: Unlike Case 1 with a total strategic default in case of a micro-insurance payout, as discussed earlier, the microfinance literature has found low default rates. In addition, our RCT sample also has a low default rate of 0.13 (see Table 7). Therefore, in this case, we consider a low strategic default probability of $\lambda = 0.1$ but keep the trust to maximum to isolate the impact of defaults. The predicted application rates are 85, 84 and 68% for micro-insured, meso-insured and uninsured loans, respectively. When farmers barely default but trust the bank fully, we find that farmers are indifferent between micro- and meso-insured loans, making the IC curves almost overlap with each other and marginally higher than uninsured case.

Case 3: The literature has found that trust in financial institution matters for credit demand (e.g.; Cai et al. 2014; Cole et al. 2013). In our RCT sample, about 70% of the farmers have some level of trust in the banks (see Table 7). Since we want to isolate the impact of a more realistic trust of the bank, we set the trust parameter to $\tau = 0.7$ and reset the default probability back to $\lambda = 1$. The predicted application rates are 98, 77 and 68% for micro-insured, meso-insured, and uninsured loans, respectively. When farmers have incomplete trust in the bank and high default rates, they will prefer micro-insured loan significantly higher than meso-insured loans. In fact, as trust diminishes, the demand for the meso-insured loan approaches the uninsured loan.

Case 4: In this case, we attempt to make a more realistic case by combining Cases 2 and 3, such that farmers have incomplete trust in the bank and lower default rates, i.e. $\tau = 0.7$ and $\lambda = 0.05$. The predicted application rates based on the Monte Carlo simulation are 85, 77 and 68% for micro-insured, meso-insured and uninsured loans, respectively. Therefore, we find that the lower trust and default brings both micro-and meso-insured ICs lower because as mentioned earlier, lower default and trust rates make the micro-insured loans and meso-insured loans less attractive, respectively. Therefore, the interaction between lower default and trust rates makes the micro-and meso-insured loans similar in nature for the farmer such that we do not see a significant difference between these two curves compared to uninsured IC. Moreover, farmers with higher risk aversions will opt out of loan application.

Case 5: We speculate that insured loan application rates may differ by gender based on the evidenced differences in characteristics of female and male farmers in microfinance literature and our sample (see Table 7). To gain insights on potential differences, we consider separate models for female and male farmers. We specifically consider four key differences between female and male simulation parameters. Specifically, we find that females are significantly less likely to default and trust the bank than males. Therefore, we assume default rates $\lambda = 0.05\, and\, 0.1$ and a high trust parameter $\tau = 0.3\, and\, 0.6$ for females and males, respectively.[6] Moreover, females have lower endowment compared to males which means that for the same amount of bank collateral requirement, females will draw a higher marginal utility from the collateral than males. [7] To reflect this, we assume collateral values of $\mathrm{C} = 0.7\, and\, 0.4$ for females and males, respectively. Lastly, due to the well-documented high repayment rates among women borrowers, we assume that banks have higher approval rates for women even in the micro-insured and uninsured cases but the meso-insured approval rates are the same at 0.9 due to the impossibility of strategic default in the latter case. Therefore, so we assume $P_U = 0.8\, and\, 0.6, P_{IC} = 0.8\, and\, 0.9$, for females and males, respectively. The simulation for female farmers shows a modest increase in application rates for micro-insured loans and no increase for the meso-insured loans relative to the uninsured loans. The predicted application rates from the simulation are 87, 62 and 61% for micro-

[6] These numbers do not match our data exactly since simulations are clearer with higher gender differences. For example, 35% of females fully trust the bank compared to 41% of males and 10% of the females have ever defaulted compared to 16% of males, which are significant at 5% level (see Table 7).

[7] As defined earlier, with a higher collateral value, we are not assuming that females have a larger collateral requirement from the bank, rather, we are attempting to capture the larger relative valuation of the collateral requirement on females given their lower wealth endowments. In fact, we find a significantly higher collateral value for females in our sample. We calculate collateral value by dividing the savings amount with the bank with the sum of savings amount, agricultural income, and remittances. We find that females have .07 collateral value, compared to .05 for males which is significantly different at 5% level (see Table 7).

insured, meso-insured and uninsured loans, respectively. Alternatively, the simulation for male farmers shows a slight increase in application rates for micro-and meso-insured loans relative to the uninsured loans. The predicted application rates are 86, 73 and 65% for micro-insured, meso-insured and uninsured loans, respectively. The overall differences between the predictions over gender and loan types demonstrate that the micro-insured loans have a significantly larger impact on application rates and meso-insured loans will have no significant differences in application rates for females compared to males.

Based on the model simulations, we make the following testable predictions:

Proposition 1 – While lower default decreases the likelihood of loan application for micro-insured loans, lower trust decreases application rates for meso-insured loans, bringing the two application rates close to each other. This combined effect will thus make the micro-and meso-insured application rates almost indifferent to each other and slightly higher than uninsured loans.

Proposition 2 – For a population with higher default rates, the likelihood of loan application for micro-insured loans will increase compared to uninsured loans.

Proposition 3 – For a population with higher trust in the bank, the likelihood of loan application for meso-insured loans will increase compared to uninsured loans.

Proposition 4 – For female farmers, the likelihood of loan application for micro-insured loans will be significantly higher than male farmers relative to uninsured loans. In contrast, the likelihood of loan application for meso-insured loans will be moderately lower for female farmers than male farmers relative to uninsured loans.

3.3 Model Assumptions for the Supply of Credit

Turning to the lender's perspective, we assume that lenders face an opportunity cost r' of lending K where $r' < r$ such that the bank's cost is lower than the interest rate faced by the farmer. Further assume that the bank knows that the farmer repays in the high yield state Y_H, but is unable to repay in the low yield state Y_L in the absence of insurance. In case of default, the bank gets to keep the collateral C'. Note that this collateral is simply the savings of the farmers with the banks, which is different from the collateral value of the farmer defined earlier (see Subsection 3.1 for definition). Normalizing the number of potential borrowers to 1, the expected profit of a bank from an uninsured loan, $\prod_U$, is given by:

$$\prod_U = pR + (1-p)\omega' - (1+r')K \tag{8}$$

For the micro-insured loan, the banks assume that some farmers may strategically default even in the case of insurance payout in drought state l, with the probability λ. Therefore, the expected profit for a bank from a micro-insured loan $\prod_{MI}$, with an insurance premium π, is given by:

$$\prod_{MI} = P(Y_H, h)\left(\frac{R}{q}\right) + P(Y_H, l)\left(\frac{R}{q}\right) + P(Y_L, l)\left[(1-\lambda)\left(\frac{R}{q}\right) + \lambda\omega'\right] + P(Y_L, h)\omega' - (1+r')(\pi + K) \tag{9}$$

For meso-insured loans, since there is no strategic default, the expected profit from a meso-insured loan $\prod_{ME}$, with an insurance premium π, is given by:

$$\prod_{ME} = P(Y_H, h)\left(\frac{R}{q}\right) + P(Y_H, l)\left(\frac{R}{q}\right) + P(Y_L, l)\left(\frac{R}{q}\right) + P(Y_L, h)\omega' - (1+r')(\pi + K) \tag{10}$$

3.4 Model simulations for the Supply of Credit

In this subsection, we simulate our supply side models to derive predictions about the approval behavior of banks. Specifically, we plot the expected profit functions of the banks from uninsured, micro-insured, and meso-insured loans against varying collateral values. To simulate the plots, for the parameters that overlap between the demand and supply side, we assume the same values as in Case 4 of the demand side simulation. However, we have few additional parameters: farmer's interest rate, bank's cost of lending, and loan amount, for which their definitions and values are given in Appendix (Table A.1).

To elicit the gender differential impacts of insured loans on loan approval probability, we assume that male and female farmers differ with respect to strategic default probability λ in the case of insurance payout in drought state l. In particular, the population of farmers is equally divided between females, denoted as *f,* and males, denoted as m, with the average default probability of females given by $\bar{\lambda}_f$ and that of males by $\bar{\lambda}_m$ such that $\bar{\lambda}_f = 0.05 < \bar{\lambda}_m = 0.1$. This can also be seen as the banks having a higher trust in females as females are found to be more trustworthy than men (Buchan, Croson, and Solnick 2008; Croson and Buchan 1999). This was also evident in our discussions with the banks, where they stated that they trusted females more with the loans.

Since the default parameter only exists in the micro-insured loan profit function, we will only see different profit function plots for this case. In general, banks profit the most from meso-insured loans, followed by micro-insured loans from females, and micro-insured loans for males compared to uninsured loans (see Figure A.1 in Appendix). Therefore, with micro-insured loans, a bank will be more likely to approve loans for females than males, compared to uninsured loans. However, with meso-insured loans, it is unclear what the overall gender differential impact will be. In conclusion, we add the following testable propositions based on the model:

Proposition 5 – 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 6 – While both females and males will experience a higher probability of approval for both micro- and meso-insured loans, females will experience a higher net likelihood of approval for micro-insured loans than males.

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.[8] 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 qualified to receive loans, or groups that have been denied loans for reasons other than past default; (ii) FGs located in districts that belong to low rainfall areas (between 800mm to 1100mm annually) for maximum impact of insured products; (iii) FGs whose primary or secondary crop is maize for reasons discussed above; (iv) FGs with 7 to 15 members due to logistical and budget constraints (insurance premiums are fully subsidized); and finally (v) FGs that take out a loan of less than 10,000 Ghana Cedis (GHc) so as to maintain a focus on the most low income groups.[9]

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 2 presents the number of farmer groups per district in the northern regions. Table 3 further presents a breakdown of FGs in each district and region.

[Insert Figure 2 here]

[Insert Table 3 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

[8] 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.

[9] 1 GHc = 0.293 USD as of February 2015.

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 4 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 categories are not statistically different in terms of preexisting financial, agricultural, demographic, and geographical data--areas identified in the literature (Table 5).

[Insert Table 4 here]

[Insert Table 5 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.[10,11] 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 8).

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.

[10] The three stages covered by the drought-index insurance are: germination, crop growth, and flowering.
[11] 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.

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.

4.2 Descriptive statistics

We present descriptive statistics of key variables for the baseline round (R0) and follow-up round (R1) in Table 6. 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 7. We discuss a selection of these variables in this subsection.

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, 20 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 6). 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 6 here]

We also 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 used for farming and remittances are 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 7 here]

For the gender disaggregated comparison, 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. Additionally, we find that females report significantly less in terms of ever having defaulted than males. This confirms our earlier speculation that banks may thus see females as more creditworthy in the absence of risk reducing mechanisms. In regard to the wealth variables, we find that females have significantly lower agricultural income, less cattle, and higher collateral value than males in R1, which is consistent with the literature. Similarly, we measure trust parameters such that "bank trust" is defined as those applicants that have the highest level of trust with the bank and "prefer micro" as those applicants that would prefer micro-insured loans to meso-insured loans. These make up a total of 39 and 29%, respectively. We find that while females have a significantly lower trust in the bank than males, there are no differences in preference for micro-insured loans between these two genders.

[Insert Table 8 here]

Table 8 presents mean t-test comparisons of loan application for the all samples (Panel A) and heterogeneous subsample applicants (Panel B). We define 'new' applicants as those applicants who do not have agricultural loans from the RCBs in the pre-baseline period (i.e., loan amount of zero in pre-R0); they make up a total of 27% of the sample. From Panel A, we find that the means of 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 application variable are significantly higher for both micro- and meso-insured loans for females in R1. Next, the mean of loan application variable is significantly higher for meso-insured loans for the subsample that places highest trust value to the bank in R1. The means of loan application variable for the subsample that prefer micro-loans are significantly higher for both micro-insured loans for R0 and R1. Finally, for the new applicant subsample, the means of both micro- and meso-insured loan application are significantly higher than control for both R1.

[Insert Table 9 here]

Table 9 presents mean t-test comparisons of loan approval for the all applicants (Panel A) and heterogeneous subsample applicants (Panel B). 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. 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. Finally, for new applicants, micro-insured loan has a significantly higher mean of loan approval for both R0 and 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 outstanding debt from last borrowing season, whether the respondent has savings with the RCB, the number of plots used during last growing season, remittances, risk aversion, whether loan was taken in 2014 (pre-study), bank dummies, and region dummies. 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). Including the bank dummies is important to control for bank-level heterogeneity as the banks are established primarily to serve a community with a specific language and culture. We stratified our randomization by loans taken pre-study and regions, so it is important to control for these variables to increase the model efficiency.

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 remittances, whether the farmers have savings with the bank, and risk aversion are significantly different for those farmers that applied for loans and those that did not (Table 10). Moreover, we conducted a mean t-test comparison by approval variable and found that the number of plots used in the last growing season, cattle, and outstanding debt are significantly different.

[Insert Table 10 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, 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.[12] Lastly, 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. 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 four steps. In the first step, we estimate the treatment impacts on loan application outcomes for all (Table 11). 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 dummies to control for bank-level heterogeneity in loan application and approval and rounds and regions to account for stratification in randomization. Finally, in Model 3, we add the covariates, X_{it}, discussed above. In the second step, we use the most robust specifications, i.e. Model 3, to estimate the heterogeneous treatment impacts on loan application (Table 12). In the third step, we estimate the treatment impacts on loan approval rates by following the first step (Table 13). Specifically Models 1-3 present estimations with no control variables (Model 1), bank and region dummies (Model 2), and additional covariates mentioned earlier (Model 3). In the fourth and final step, we use the most robust specifications, i.e. Model 3, to estimate the heterogeneous treatment impacts on loan approval (Table 14).

5.2.1 Treatment Impacts on Loan Application

Table 11 presents DID estimates of the treatment impacts on loan application variable for all applicants with standard errors clustered at the FG level. We progressively build efficient models by adding bank- and region-level controls in Model 2, and additional covariates in Model 3.

[Insert Table 11 here]

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

We find positive signs for the treatment impacts ranging from 7.3 to 8.2 percentage points for micro-insured loans and 5.4 to 5.9 percentage points for meso-insured loans. However, they are not statistically significant for any of the treatments. These results align well with Proposition 1, which predicts that trust and default may offset each other, resulting in insignificant impact of insured loans on farmers' loan application. This indicates that we have a sample with a low level of defaults and an incomplete trust in the bank which aligns well with the existing literature discussed earlier. In fact, in our sample, only 13% of the farmers report having ever defaulted on the agricultural loans in the past (see Table 7). For the trust variable, we ask the farmers a five-point Likert-scale of trust in the bank, ranging from least trustworthy to very trustworthy. While about 70% of the farmers state that they have some level of trust in the bank (see Table 7), we are cautious about this finding. This is because farmers are aware that the banks are our working partners for this study, so they might be overstating the trust so as not to potentially jeopardize their relationship with the banks. Moreover, because insured loans are a new product, farmers may not fully trust the bank with this new product in practice. We will unpack this speculation further in the next section. Moreover, the insignificant results could also be spurred due to the fact that we have an application rate of over 90% in the baseline period making it difficult to detect marginal increase from an already higher application rate in the baseline. Another reason for the insignificance could be that we do not have a big enough sample so we may lack the power to detect these effects.

For additional covariates in Model 3, we find that the coefficient on savings is positive and significant, indicating that FGs with savings with the bank are more likely to apply for loans. This is likely due to the savings requirement for loan approval. Similarly, the coefficient on remittances is positive and significant indicating that farmers with higher remittances are more likely to apply for loans. Additionally, compared to the farmers not at all willing to take risks, risk-loving farmers are more likely to apply for loans. These findings concur with the literature on the relationship between wealth and risk aversion and technology adoption.

5.2.2 Heterogeneous Treatment Impacts on Loan Application

Table 12 presents DID estimates of the heterogeneous treatment impacts on loan application variable with standard errors clustered at the FG level. The estimations control for bank and region dummies and additional covariates mentioned earlier. The first column presents estimates for those that prefer micro-insured loans, followed by those that highly trust the bank, female applicants, male applicants, and finally "new applicants" as those that did not apply for loans in the pre-study period as defined earlier.

[Insert Table 12 here]

While we did not find a significant impact of the treatment on loan application for the total sample, we find heterogeneous treatment impacts for subsamples of applicants. For example, micro-insured loans increase the likelihood of loan application by 19 percentage points for those applicants that prefer micro-insured loans, which is statistically significant at 10% level. This result aligns well with Prediction 2 because among those farmers that state that they prefer micro-insured loans, they prefer it due to its flexibility of using the payout in drought state for purposes other than repayments, i.e. having the choice to strategically default on their loans for smoothing consumption. In contrast, meso-insured loans increase the likelihood of loan application by 11 percentage points for those applicants that highly trust the bank, which is statistically significant at 10% level. These results confirm Proposition 3 in that we find a significant increase in loan application probability for meso-insured loans for those with a high level of trust in the bank. For new applicants, the magnitudes for both treatment impacts are large and insignificant, which may be due to the fact that the sample size is too small.

When it comes to gender differential impacts of insurance, we find that micro-insured loans increase the likelihood of application for females by 15 percentage points which is significant at 10% level. While meso-insured loans have no significant increase for females, we note that the magnitude of coefficient is the same as that of the subsample that highly trust the bank. These results indicate that while female farmers may want the option of managing the payouts potentially for purposes other than repayments, their preference for micro-insured loans is mainly influenced by the fact that they have a lower trust in the bank. In fact, as noted earlier, mean t-test comparison between females and males show that females have significantly lower default rates and are less likely to trust the bank than males (Table 7). In this sense, we speculate that the preference for micro-insured loans for female farmers may not spur from defaulting, but rather, from distrusting the bank to use the insurance payouts to forgive their loans. Moreover, in our sample, we find that females have lower endowment and their collateral value is higher than 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).

Our results partially confirm Proposition 4 which predicted that for female farmers, the likelihood of loan application for micro-insured loans will be significantly higher than male farmers relative to uninsured loans. The results do not confirm the second part of the prediction that for female farmers, the likelihood of loan application for meso-insured loans will be lower than males, compared to uninsured loans.

5.2.3 Treatment Impacts on Loan Approval

Table 13 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 bank- and region-level controls in Model 2 and additional covariates in Models 3.

[Insert Table 13 here]

For all applicants, we find that the impacts of micro-insured loans range from 8.4 to 11 percentage points, however, they are not statistically significant (Models 1-3). In contrast, for meso-insured loans, we find that the estimated impacts are large, positive, and statistically significant at the 5% level and range from 21 to 24 percentage points. These results partially corroborate our theoretical prediction in Proposition 5 such that meso-insured loans significantly increase the likelihood of a farmer's loan approval, but not micro-insured loans. While theoretically loan approval should increase with micro-insured loans due to the insurance payout, farmers get the insurance payouts in case of a drought and banks may lack confidence that the FGs will use the payouts for repaying the loan. Instead, farmers could use the payout for consumption smoothing. If this is the case, then banks will treat farmers with micro-insured loans no differently than those with uninsured loans. Alternatively, our sample size may not have enough power to statistically detect the significance of micro-insured loans. Besides the treatment impacts, Model 3 shows that having outstanding debt adversely impacts the likelihood of approval, while the number of agricultural plots and having a loan in the pre-study period are positively correlated with loan approval probability.

5.2.4 Heterogeneous Treatment Impacts on Loan Approval

Table 14 presents DID estimates of the heterogeneous treatment impacts on loan approval variable with standard errors clustered at the FG level. The estimations control for bank and region dummies and additional covariates mentioned earlier. The first column presents estimates for female applicants, followed by male applicants, and finally "new applicants" as those that did not apply for loans in the pre-study period as defined earlier.[13]

[Insert Table 14 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 coefficient for females are marginally insignificant and at 22 percentage points. When we only control for the

[13] Note that we cannot conduct the heterogeneous impact estimation for trust bank and prefer micro applicants because these are farmer's attributes that would not affect the bank's decision of loan approval.

stratification variables, loan status in 2014 and region, and additional covariates, but not banks, meso-insured loan impact is a 24 percentage points increase in the likelihood of application for females, which is significant at 10% level (Table A.2, Appendix). For male farmers, we find that the coefficient of meso-insured loans is positive at 27 percentage points and significant at 5% level. These results partially confirm our Proposition 6 in that both females (marginally) and males experience a higher probability of approval for meso-insured loans, but not for micro-insured loans. We speculate that banks may perceive the micro-insured and uninsured loans in the same light if they do not trust that the farmers will use the payout in the drought state to make repayments on their loans. Alternatively, we cannot reject the possibility that our sample size may not have enough power to detect the statistical significance of these impacts. Additionally, while our theoretical model does not predict on the gender differential impact of meso-insured loans on approval, in reality, the issue of trust from the banks to the farmers may be playing a role in reducing the risk of defaults, particularly for male farmers. This could explain why meso-insured loans benefit male farmers more than female farmers, especially as the former are seen as both less trustworthy and creditworthy (Buchan, Croson, and Solnick 2008; Croson and Buchan 1999; Sharma and Zeller 1997; D'Espallier, Guérin, and Mersland 2011).

6 Conclusion and Policy Implications

Sixty percent 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 no evidence that insured loans have a significant impact on loan application on average. However, we find that micro-insured loans increase the likelihood of loan application among female farmers. Moreover, among the subsample of applicants who prefer micro-insured loans, they are more likely to apply for the same, possibly because of its flexibility to use the payouts for either repayment or consumption smoothing in a drought state.

Conversely, the subsample of applicants with the highest level of trust in the bank are more likely to apply for meso-insured loans. We speculate that since female farmers have significantly lower endowment and lower trust in the bank than males, female farmers might value micro-insured loans more due to its flexibility of smoothing consumption in the drought state and not trusting the bank to forgive their loans in the meso-insured case. Our evidence from trust, or lack thereof, as a barrier to insured loans is consistent with Cai et al. (2014) and Cole et al. (2013). Additionally, we believe that the positive but mostly insignificant results for the total sample could also be because our sample is largely drawn from a sample with low default and trust in the bank as well as 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. However, we caution that the provision of insured loans themselves are not a sufficient condition for increasing demand for credit, rather, it should be introduced with complimentary services that will boost the uptake. For example, to protect the most vulnerable farmers from defaulting and to help with consumption smoothing in case of a drought, the insured loans should be accompanied with an income insurance such that farmers (banks) can use (give) part of the payout for consumption smoothing. Another way to boost application rates, especially for meso-insured loans is by introducing activities that will build trust between the farmers and the banks such as face-to-face meetings between the farmers, banks, and insurance companies. In our study, we conducted a capacity building meeting between the extension agents, RCBs, and GAIP, but not the farmers due to budget limitations.

A major finding of the paper is that insuring agricultural loans in a way that guarantees full loan repayment during a drought 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 the total sample, with a higher impact for male farmers. We speculate that the net higher likelihood of approval for males in the meso-insured loans is because of the fact that males are otherwise seen as both less creditworthy and trustworthy (Buchan, Croson, and Solnick 2008; D'Espallier, Guérin, and Mersland 2011). Therefore, holistic policies that protect farmers from defaulting, help with their consumption smoothing, and build trust among the banks and farmers can potentially boost banks' loan approval rates even with micro-insured loans. Taken together, our findings indicate that reducing systemic risk for borrowers and lenders can serve as a springboard to expanded credit access (from both demand and supply sides) and associated efficiency-enhancing technology adoption that is desperately needed in SSA countries.

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FIGURES AND TABLES

Table 1: Definition of base parameters of the model and value for the base case

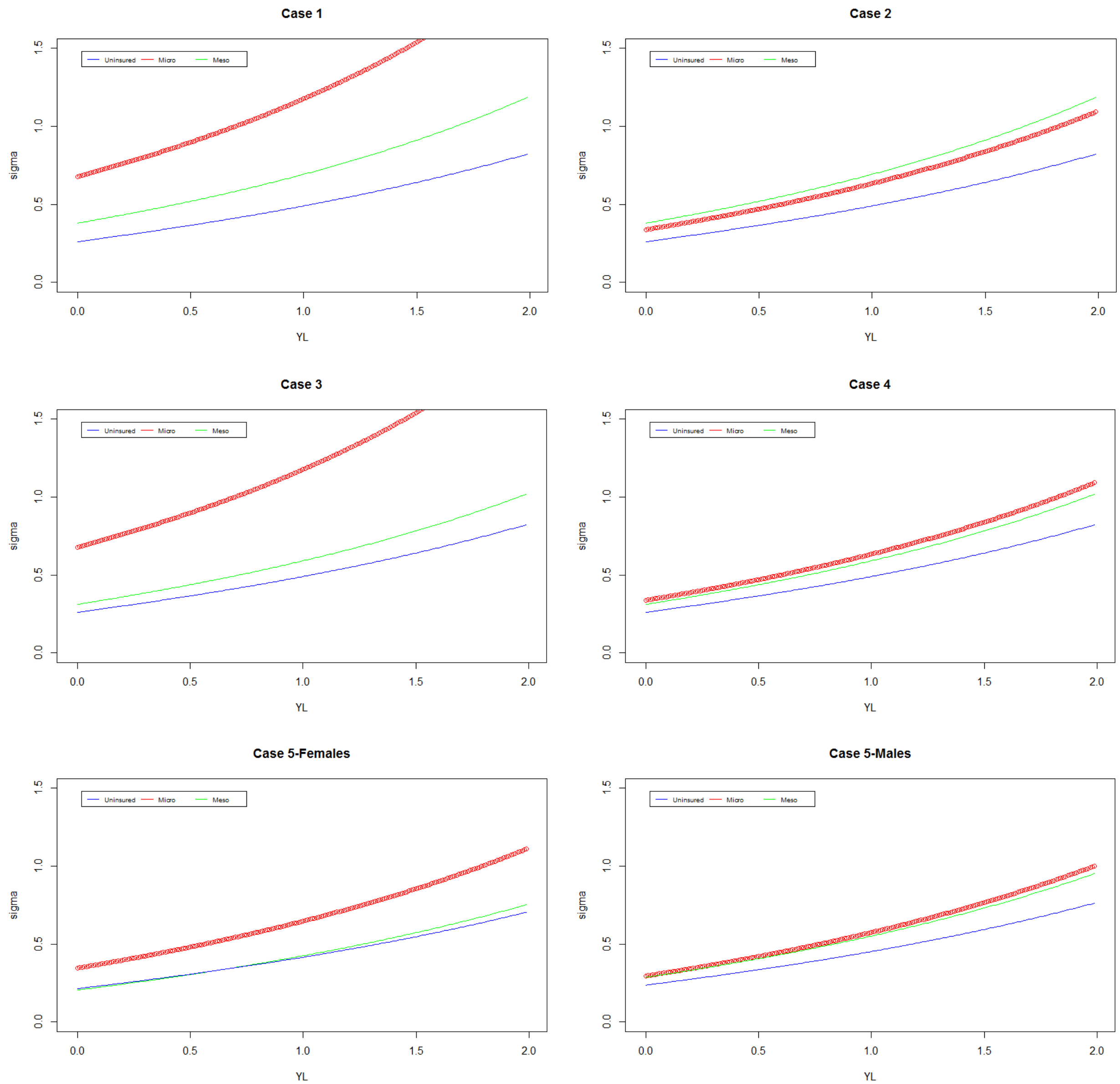
Parameters	Definition	Value
ω	Asset parameter	1
ρ	Correlation between output and rain states	.9
p	Probability of high output	.5
q	Probability of high rain	.5
τ	Value of trust in the bank	1
R	Loan plus interest	1
φ	Penality for default	.7
κ	Cost of application	.1
Y_H	High yield with improved technology	15
Y_L	Low yield with improved technology	$[(\varphi+\kappa)+0.01\,,\frac{R}{q}-0.01]$
Y_t	Output with traditional seed	5
C	Collateral value	.2
P_{ME}	Probability of approval for meso-insured loans	.9
P_{MI}	Probability of approval for micro-insured loans	.7
P_U	Probability of approval for uninsured loans	.6
λ	Proportion of population strategically defaulting	1

Table 2: Heteregeneity in base parameter values and corresponding predicted application rates

Parameter	Case 1	Case 2	Case 3	Case 4	Case 5 – Females	Case 6 – Males
Panel A: Heteregeneity in base parameter values						
τ	1	1	**.7**	**.7**	**.3**	**.6**
C	.2	.2	.2	.2	**.7**	**.4**
P_{ME}	.9	.9	.9	.9	.9	.9
P_{MI}	.8	.8	.8	.8	**.8**	**.7**
P_U	.7	.7	.7	.7	**.8**	**.6**
λ	1	**.1**	1	**.1**	**.05**	**.1**
Panel B: Simulation Results of application rates						
Micro	.9865	.8535	.9859	.8544	.8679	.8581
Meso	.8386	.8367	.7687	.7666	.6209	.7339
Uninsured	.6833	.6832	.6849	.6830	.6118	.6462

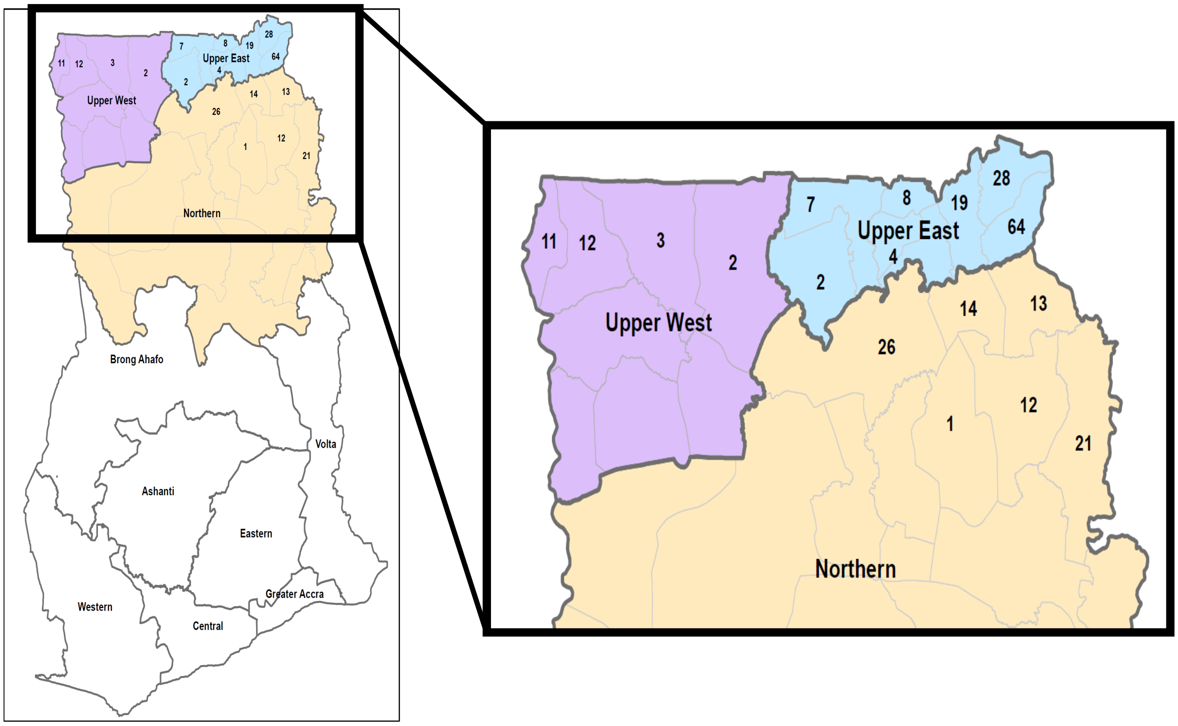
Application simulations assume $Y_L = 1$, and a population of idividuals with CRRA coefficients drawn from a normally distribution with mean μ= .3 and standard deviation $\sigma = .3$, and sample size N=100000

Figure 1: Indifference curves between no loan and loan for with and without insurance



Case 1 is the naïve case with full trust in the bank and high strategic default; Case 2 is with full trust and low defaults; Case 3 is with low trust and high defaults; Case 4 is with low trust and low default; Case 5-Females are with both low trust and defaults but high collateral value; and finally Case 5-Males are with trust and default higher than females but lower collateral value.

Figure 2: 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 3: Farmer Groups by Regions and Districts

Districts	No. of farmer groups
Northern	*98*
Bonkpirigu Yongyong	13
Chereponi	11
Gushegu	12
Karaga	1
Mamprugu Moagduri	2
Mamprusi East	10
Mamprusi West	28
Saboba	21
Upper East	*132*
Bawku Municipal	14
Bawku West	19
Binduri	14
Bolgatanga Municipal	4
Bongo	8
Builsa North	1
Builsa South	1
Garu Tempane	64
Kassena Nankana East	4
Kassena Nankana West	3
Upper West	*28*
Jirapa	7
Lambussie Karni	5
Lawra	1
Nandom	10
Sissala East	2
Sissala West	3
Total	258

Table 4: 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 5: One-way analysis of variance (ANOVA) across Control and Treatment categories

	Category	Mean	Std.	P-Value
Maize quantity (KGs)				.18
	Control	1152	2260	
	Treatment 1	1326	4755	
	Treatment 2	816	989	
Fertilizer quantity (Packet)				.98
	Control	.86	.35	
	Treatment 1	.86	.35	
	Treatment 2	.86	.34	
Hybrid binary (1=use)				.81
	Control	.15	.35	
	Treatment 1	.15	.36	
	Treatment 2	.13	.34	
Number of loans taken from formal and informal sources				.84
	Control	.66	.63	
	Treatment 1	.63	.62	
	Treatment 2	.64	.62	
Agricultural loan amount from the bank (GHc)				.38
	Control	360	194	
	Treatment 1	378	396	
	Treatment 2	334	182	
Default binary (1=defaulted)				.84
	Control	.16	.37	
	Treatment 1	.15	.36	
	Treatment 2	.17	.38	
Total income (GHc)				.62
	Control	2269	1592	
	Treatment 1	2210	1441	
	Treatment 2	2141	1434	
Agricultural income (GHc)				.52
	Control	1453	1002	
	Treatment 1	1426	941	
	Treatment 2	1351	935	
Time taken to input market (Minutes)				.78
	Control	83.5	83.1	
	Treatment 1	80.7	69.4	
	Treatment 2	85.9	101.0	
Aggregator binary (1=sell via aggregator)				.59
	Control	.36	.48	
	Treatment 1	.40	.49	
	Treatment 2	.36	.48	
Good season (1=2014 was a good season)				.91
	Control	.40	.49	
	Treatment 1	.42	.49	
	Treatment 2	.40	.49	
Risk aversion (Likert Scale 1-5)				.67
	Control	2.1	1.1	

Treatment 1	2.1	1.0	
Treatment 2	2.2	1.1	
Maize planted land (Acres)			.30
Control	2.9	3.1	
Treatment 1	3.1	4.8	
Treatment 2	2.6	2.4	
Number of household members			.30
Control	8.6	3.2	
Treatment 1	8.4	3.3	
Treatment 2	8.2	3.4	
Medical emergency (frequency)			.47
Control	3.1	4.3	
Treatment 1	2.6	4.3	
Treatment 2	2.7	4.1	
Borrow cash/in-kind (frequency)			.55
Control	.57	.99	
Treatment 1	.62	1.0	
Treatment 2	.52	.99	
Death (frequency)			.95
Control	.44	.85	
Treatment 1	.43	.77	
Treatment 2	.45	.86	
Festival (frequency)			.89
Control	.87	1.3	
Treatment 1	.86	1.3	
Treatment 2	.82	1.3	
Crop loss (frequency)			.57
Control	.32	.94	
Treatment 1	.32	.67	
Treatment 2	.26	.54	
Cash loan (1=prefer loan in cash)			.36
Control	.56	.50	
Treatment 1	.50	.50	
Treatment 2	.52	.50	
Price of maize (GHc/ KG)			.45
Control	1.00	.43	
Treatment 1	1.04	.41	
Treatment 2	.98	.35	
Remittance (GHc)			.25
Control	115	.44	
Treatment 1	100	.41	
Treatment 2	86	.35	
Proportion of plots planted with maize			.33
Control	.42	.22	
Treatment 1	.42	.24	
Treatment 2	.45	.40	
District			.47
Control	11	6.6	

Treatment 1	12	7.3
Treatment 2	11	6.8

Table 6: 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 (GHc)	1413	959	1333	885	.86
No. of plots used	3	1.04	3.9	2.0	.00
Cattle	3.5	4.95	4.2	14.3	.22
Remittances (GHc)	100	204	124	223	.03
Saving (GHc)	357	504	330	426	.25
Debt (1=outstanding debt)	.20	.40	.32	.47	.00
Respondent age	45	13	46	13	.12
No. of HH members	8	3	10	6	.00
No. of help in case of draught	2.4	3.3	1.8	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	.78				
Primary education	.05				
Middle school	.06				
High School	.07				
College or more	.04				

Table 7: Pairwise Mean Comparisons for Males and Females by Round

	Round 0			Round 1		
	Females	Males	P-value	Females	Males	P-value
Credit access parameters						
Loan application	.94	.90	.04	.81	.79	.51
Loan approval	.77	.75	.59	.76	.81	.13
Wealth parameters						
Agric. inc. (GHc)	1209	1525	.00	1250	1473	.00
Number of Plots	2.97	3.03	.63	3.70	4.08	.00
Cattle	2.85	4.12	.00	3.15	5.10	.02
Remittance (GHc)	109	110	.47	105	125	.49
Amt. saved (GHc)	353	361	.84	303	361	.00
Collateral value	.07	.05	.04	.10	.06	.00
Risk parameters						
Draught help	2.1	2.0	.50	1.9	1.8	.55
Good season 5	2.3	2.4	.52	2.4	2.5	.04
Risk aversion	2.19	2.08	.14	---	---	
Trust parameters						
Bank trust	---	---		.35	.41	.01
Prefer meso to micro	---	---		.71	.71	.82

Amount saved is the savings with the bank; Collateral value is calculated by dividing Amount saved with the total liquid wealth (agricultural income, remit and amount saved) and multiplied by 100 for scaling; 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; Risk aversion is a 5-point Likert Scale measured during baseline; Bank trust is a dummy variable equal to one for those that trust the bank very much.

Table 8: Pairwise Mean Comparisons for All and Heterogeneous Applicants

Variables	Control	Treatment1	(Micro)	Treatment2	(Meso)
PANEL A – LOAN APPLICATION PROBABILITIES FOR ALL SAMPLE					
Loan Application All Round 0	.9189	.9310		.8957	
Loan Application All Round 1	.7567	.8506	***	.7915	
PANEL B - LOAN APPROVAL PROBABILITIES FOR HETETOGENEOUS SAMPLE					
Female Applicants Round 0	.9459	.9440		.9212	
Female Applicants Round 1	.7207	.8800	***	.8189	*
Male Applicants Round 0	.8986	.9191		.8712	
Male Applicants Round 1	.7834	.8235		.7651	
Trust Bank Applicants Round 0	.9592	.9630		.9271	
Trust Bank Applicants Round 1	.8265	.8981		.9271	**
Prefer Micro Applicants Round 0	.9638	.8888	*	.8970	
Prefer Micro Applicants Round 1	.6988	.8472	**	.7647	
Loan Application New Round 0	.8209	.8333		.7826	
Loan Application New Round 1	.6418	.8333	***	.7826	*

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

Table 9: Pairwise Mean Comparisons of Loan Approval Variable for All and Heterogeneous Applicants

	Control	Treatment1	(Micro)	Treatment2	(Meso)
PANEL A – LOAN APPLICATTION PROBABILITIES FOR ALL APPLICANTA					
Loan Approval All Round 0	.7689	.7901		.7241	
Loan Approval All Round 1	.6888	.8243	***	.8536	***
PANEL B –LOAN APPROVAL PROBABILITIES FOR HETEROGENEOUS SUBAMPLE APPLICANTS					
Female Approvals Round 0	.7523	.8135		. 7436	
Female Approvals Round 1	.6125	.8364	***	. 8077	***
Male Approvals Round 0	.7819	.7680		. 7043	
Male Approvals Round 1	.7414	.8125		.9010	***
Loan Approval New Round 0	.0545	.20	**	0	
Loan Approval New Round 1	.4884	.70	**	.50	

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

Table 10: Pairwise Mean T-test Comparisons for key variables by application/approval status for the baseline

	Apply	Did not Apply	Difference
Agric. Inc. (GHc)	1543	1400	
No. of plots used	3.2	3.0	
Cattle	4.4	4.0	
Remittances (GHc)	39	106	**
Saving binary	.57	.68	*
Respondent age	44	45	
Drought help	2.2	2.0	
Good Season 5	2.3	2.4	
Risk aversion	2.4	2.1	**
Debt	.23	.20	
	Approve	Did not Apply	Difference
Agric. Inc. (GHc)	1471	1379	
No. of plots used	2.8	3.0	**
Cattle	5.1	3.6	**
Remittances (GHc)	82	113	*
Saving binary	.72	.67	
Respondent age	45	45	
Draught help	1.8	2.0	
Good season 5	2.4	2.4	
Risk aversion	1.8	2.2	***
Debt	.25	.18	**

*** 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 11: Linear Probability Model Treatments Impacts on Loan Application

VARIABLES	Model 1	Model 2	Model 3
Treatment 1	0.012	0.012	0.010
	(0.040)	(0.040)	(0.041)
Treatment 2	-0.023	-0.023	-0.024
	(0.044)	(0.045)	(0.046)
Round 1	-0.162***	-0.410***	-0.705***
	(0.052)	(0.156)	(0.209)
Treatment1*Round1	0.082	0.074	0.073
	(0.066)	(0.065)	(0.066)
Treatment2*Round2	0.058	0.059	0.054
	(0.071)	(0.071)	(0.071)
Debt from last season (1=yes)			-0.038
			(0.045)
Bank saving binary (1=yes)			0.047**
			(0.024)
No. of plots used for farming			-0.011
			(0.007)
Remittance/100 (GHc)			0.012***
			(0.004)
Risk aversion Likert-scale (1-5)			
Very willing to take risks			0.282*
			(0.165)
Willing to taking risks			0.326**
			(0.164)
Indifferent to take risks			0.224
			(0.170)
Not willing to take risks			0.270*
			(0.160)
Bank loan taken 2014 (1= yes)			0.070
			(0.066)
Constant	0.919***	0.919***	0.917***
	(0.029)	(0.030)	(0.044)
Bank dummies	No	Yes	Yes
Region dummies	No	Yes	Yes
Observations	1,558	1,558	1,558
R-squared	0.034	0.101	0.122

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks and 3 northern regions have been included in the dummy; Upper west region is the baseline; Not at all willing to take risks is the baseline for Risk aversion variable.

Table 12: Heterogeneous Linear Probability Model Treatments Impacts on Loan Application

VARIABLES	Prefer Micro	Trust Bank	Females	Males	New Applicants
Treatment 1	-0.101	-0.008	-0.010	0.022	-0.037
	(0.063)	(0.037)	(0.044)	(0.058)	(0.126)
Treatment 2	-0.089	-0.040	-0.030	-0.027	-0.051
	(0.058)	(0.043)	(0.048)	(0.062)	(0.124)
Round 1	-1.010**	0.073	-0.669**	-0.708***	-0.744***
	(0.397)	(0.126)	(0.264)	(0.255)	(0.107)
Treatment1*Round1	0.189*	0.039	0.149*	0.002	0.222
	(0.106)	(0.070)	(0.082)	(0.080)	(0.140)
Treatment2*Round2	0.139	0.113*	0.113	0.007	0.145
	(0.098)	(0.067)	(0.090)	(0.088)	(0.147)
Debt from last season (1=yes)	-0.123*	-0.085	-0.049	-0.036	-0.072
	(0.067)	(0.057)	(0.047)	(0.066)	(0.124)
Bank saving binary (1=yes)	0.063*	0.021	0.051*	0.057*	0.130**
	(0.036)	(0.032)	(0.028)	(0.032)	(0.058)
No. of plots used for farming	-0.020	-0.014	-0.015	-0.007	-0.033**
	(0.016)	(0.009)	(0.010)	(0.008)	(0.016)
Remittance/100 (GHc)	0.014**	0.007	0.013**	0.011**	0.031***
	(0.007)	(0.005)	(0.005)	(0.005)	(0.009)
Risk aversion Likert-scale (1-5)					
Very willing to take risks	0.486	-0.022	0.118	0.399*	0.295
	(0.323)	(0.060)	(0.163)	(0.220)	(0.191)
Willing to taking risks	0.513	-0.022	0.161	0.448**	0.420**
	(0.321)	(0.048)	(0.160)	(0.221)	(0.193)
Indifferent to take risks	0.467	-0.034	-0.034	0.440*	0.161
	(0.316)	(0.062)	(0.165)	(0.230)	(0.209)
Not willing to take risks	0.581*		0.029	0.472**	0.383*
	(0.319)		(0.166)	(0.217)	(0.198)
Bank loan taken 2014 (1= yes)	0.159	-0.020	0.173*	0.032	---
	(0.104)	(0.076)	(0.091)	(0.078)	---
Constant	1.009***	1.001***	0.958***	0.879***	0.842***
	(0.064)	(0.051)	(0.048)	(0.059)	(0.103)
Bank dummies	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	446	604	726	832	416
R-squared	0.232	0.117	0.224	0.106	0.247

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks and 3 northern regions have been included in the dummy; Upper west region is the baseline; Not at all willing to take risks is the baseline for Risk aversion variable. Trust bank refers to the subsample of population which trusts banks very highly; Prefer Micro are the subsample that prefers micro-insured loans to micro-insured loans; and New Applicants are those that did not have a loan in 2014.

Table 13: Linear Probability Model Treatments Impacts on Loan Approval

VARIABLES	Model 1	Model 2	Model 3
Treatment 1	0.021	0.021	0.010
	(0.066)	(0.066)	(0.067)
Treatment 2	-0.045	-0.045	-0.064
	(0.070)	(0.071)	(0.070)
Round 1	-0.080	0.112	0.142
	(0.069)	(0.078)	(0.124)
Treatment1*Round1	0.114	0.084	0.107
	(0.088)	(0.089)	(0.096)
Treatment2*Round2	0.210**	0.220**	0.239**
	(0.088)	(0.087)	(0.093)
Debt from last season (1=yes)			-0.124**
			(0.060)
Bank saving binary (1=yes)			-0.020
			(0.028)
No. of plots used for farming			0.024***
			(0.008)
Remittance/100 (GHc)			0.005
			(0.005)
Risk aversion Likert-scale (1-5)			
Very willing to take risks			-0.322***
			(0.069)
Willing to taking risks			-0.211***
			(0.060)
Indifferent to take risks			-0.186***
			(0.069)
Not willing to take risks			-0.239***
			(0.069)
Loan status binary (1= yes in 2014)			0.231***
			(0.070)
Constant	0.769***	0.769***	0.741***
	(0.048)	(0.048)	(0.061)
Bank dummies	No	Yes	Yes
Region dummies	No	Yes	Yes
Observations	1,336	1,336	1,336
R-squared	0.017	0.110	0.158

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks and 3 northern regions have been included in the dummy; Upper west region is the baseline; Not at all willing to take risks is the baseline for Risk aversion variable.

Table 14: Heterogeneous Linear Probability Model Treatments Impacts on Loan Approval

VARIABLES	Females	Males	New Applicants
Treatment 1	0.040	-0.018	0.137
	(0.085)	(0.085)	(0.097)
Treatment 2	-0.035	-0.093	-0.064
	(0.092)	(0.090)	(0.049)
Round 1	0.312*	0.079	0.891***
	(0.158)	(0.139)	(0.125)
Treatment1*Round1	0.130	0.091	-0.074
	(0.137)	(0.115)	(0.159)
Treatment2*Round2	0.218	0.267**	0.110
	(0.132)	(0.112)	(0.095)
Debt from last season (1=yes)	-0.125*	-0.116	-0.065
	(0.074)	(0.078)	(0.093)
Bank saving binary (1=yes)	-0.060	0.006	0.001
	(0.038)	(0.038)	(0.042)
No. of plots used for farming	0.029**	0.014	-0.005
	(0.012)	(0.010)	(0.012)
Remittance/100 (GHc)	0.006	0.004	-0.024**
	(0.007)	(0.007)	(0.010)
Risk aversion Likert-scale (1-5)			
Very willing to take risks	-0.426***	-0.222**	-0.131**
	(0.108)	(0.092)	(0.066)
Willing to taking risks	-0.284***	-0.152*	-0.001
	(0.097)	(0.083)	(0.036)
Indifferent to take risks	-0.309***	-0.078	0.145
	(0.106)	(0.109)	(0.131)
Not willing to take risks	-0.292***	-0.203*	
	(0.100)	(0.103)	
Loan status binary (1= yes in 2014)	0.243**	0.205**	---
	(0.100)	(0.084)	---
Constant	0.748***	0.755***	0.111**
	(0.083)	(0.076)	(0.053)
Bank dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Observations	634	702	326
R-squared	0.198	0.157	0.714

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Fourteen rural community banks and 3 northern regions have been included in the dummy; Upper west region is the baseline; Not at all willing to take risks is the baseline for Risk aversion variable. Trust bank refers to the subsample of population which trusts banks very highly; and New Applicants are those that did not have a loan in 2014.

APPENDIX

A.1 Demand Side Theory Calculations

At actuarially priced premium, we have

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

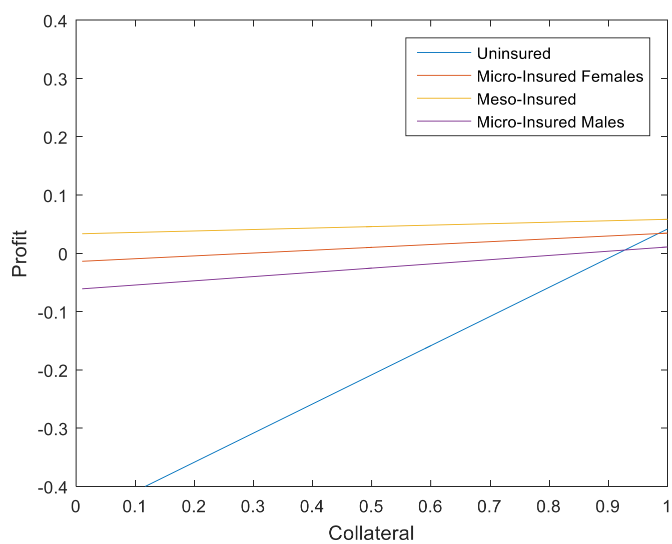
Then, since $R = (1+r)K$ and $\pi = \frac{1-q}{q}K$, we have:

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

Table A.1: Definition of parameters and their value for Demand Side Profit Models

Parameters	Definition	Value
r	Interest rate for the farmers	.2
r'	Bank's internal cost of lending K	.15
p	Probability of high output	.5
q	Probability of high rain	.5
K	Loan amount	0.83
ω	Collateral value	[0, 1]
λ	Proportion of females strategically defaulting	.05
λ	Proportion of males strategically defaulting	.1
π	Insurance premium for the loans	$\left(\frac{1-q}{q}\right)K$

Figure A.1: Bank profits between insured and uninsured loans



The orange curve is the bank profit from uninsured loans, red from micro-insured loans for females, purple from micro-insured loans from males, and blue from uninsured loans.

Table A.2: Heterogeneity in Linear Probability Model Treatments Impacts on Loan Approval

VARIABLES	Females	Males	New Applicants
Treatment 1	0.035	-0.018	0.075
	(0.084)	(0.083)	(0.100)
Treatment 2	-0.041	-0.090	-0.098
	(0.090)	(0.089)	(0.062)
Round 1	0.077	0.084	0.817***
	(0.140)	(0.143)	(0.149)
Treatment1*Round1	0.159	0.091	0.010
	(0.139)	(0.121)	(0.168)
Treatment2*Round2	0.244*	0.267**	0.068
	(0.130)	(0.121)	(0.161)
Debt from last season (1=yes)	-0.159**	-0.090	-0.195***
	(0.065)	(0.065)	(0.071)
Bank saving binary (1=yes)	-0.033	0.010	0.095*
	(0.039)	(0.040)	(0.052)
No. of plots used for farming	0.033***	0.007	-0.012
	(0.011)	(0.011)	(0.016)
Remittance/100 (GHc)	0.006	0.002	-0.007
	(0.006)	(0.007)	(0.013)
Risk aversion Likert-scale (1-5)			
Very willing to take risks	-0.365***	-0.257***	-0.080
	(0.078)	(0.085)	(0.101)
Willing to taking risks	-0.183***	-0.163**	0.106
	(0.060)	(0.082)	(0.086)
Indifferent to take risks	-0.233***	-0.090	0.160
	(0.068)	(0.107)	(0.171)
Not willing to take risks	-0.217***	-0.234**	
	(0.073)	(0.094)	
Loan status binary (1= yes in 2014)	0.334***	0.248***	
	(0.087)	(0.077)	
Constant	0.729***	0.772***	0.113*
	(0.080)	(0.076)	(0.064)
Bank dummies	No	No	No
Region dummies	Yes	Yes	Yes
Observations	634	702	326
R-squared	0.146	0.084	0.495

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at group level and are in parentheses. Upper west region is the baseline for regional dummy; Not at all willing to take risks is the baseline for Risk aversion variable. Trust bank refers to the subsample of population which trusts banks very highly; and New Applicants are those that did not have a loan in 2014.