CAN INDEX INSURANCE IMPROVE CREDIT ACCESS AMONG SMALLHODLER FARMERS IN GHANA? DOES IT DIFFER OVER MALE AND FEMALE FARMERS?

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ABSTRACT

The majority of the world's poor live in rural areas and rely on agriculture for their income. Therefore, increasing agricultural efficiency via technology adoption is critical to reducing poverty in developing agrarian economies such as those in Sub-Saharan Africa (SSA). Despite its apparent advantages, SSA has one of the lowest adoption rates. Accordingly, the objective of this paper is to investigate if the availability of meso-and micro-level insurance encourages access to credit by relaxing demand side and supply side constraints. We further disaggregate the effects by gender of the farmer to see if any differential impacts exist over female versus male farmers. Using a randomized control trial and difference-in-difference estimation, we find that availability of meso-level insurance, when the banks are the policy holders, increases the likelihood of agricultural loan approvals for smallholder farmers. Gender level analysis shows that the likelihood increases for both female and male farmers.

Key Words – agricultural technology adoption, credit access, insurance, panel data, Ghana

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1. INTRODUCTION

Increasing agricultural efficiency is a key to reducing poverty in developing agrarian economies such as those in Sub-Saharan Africa (SSA). Agriculture sector plays an important role in SSA, in terms of employment, making the sector crucial to economic development (World Bank 2008). In fact, improvements in agricultural technology has been shown to be a key mechanism for reducing rural poverty and improving household well-being in developing agrarian economies (Bourdillon et al. 2003; Mendola 2007; Kijima, Otsuka, and Sserunkuuma 2008; Kassie, Shiferaw, and Muricho 2011). Despite these advantages, SSA countries have lowest rates of technology adoption (Tripp and Rohrbach 2001). Among farmers with low adoption rates, female farmers form the majority, posing a hindrance to agricultural efficiency, where 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 compared to male farmers (Aguilar et al. 2015; Kilic, Palacios-López, and Goldstein 2015). Leveling the field of access to agricultural resources including technology for male and female farmers could increase female farmers' agricultural yields by 20-30%, increasing the total output by 4% and reducing 12–17 % of the world's hunger (FAO 2011).

Numerous constraints to the adoption of technologies have been documented, for example, high transaction costs, low financial liquidity, seasonality, and risk rationing (Croppenstedt, Demeke, and Meschi 2003; Suri 2011). This is particularly true for female headed households due to their lack of access and ownership of agricultural resources, ways to ensure themselves against systematic shocks, and credit constraints (Gladwin 1992; Khandker 1998; Quisumbing and Pandolfelli 2010). Central to these constraints is the absence of access to credit required to finance lumpy seasonal input purchases from both demand and supply sides. On the demand side, farmers are often unable to obtain credit because they lack collateral or they risk losing their assets (pledged as collateral) in case of an adverse shock (Hertz 2009; Marra, Pannell, and Abadi Ghadim 2003; Mude and Barrett 2012).On the supply side, banks are reluctant to supply loans to subsistence farmers who are perceived as riskier clients due in part to undiversifiable systemic weather risk such as insufficient rainfall. For these reasons, an insurance product designed to protect against irregular rainfall patterns that is properly integrated into the financial market may improve access to credit for small holder farmers.

Theoretical modeling have shown that index insurance, especially at the meso-level (e.g., micro-finance institutions, farmers' cooperatives, input suppliers), where the indemnity goes to the risk aggregator rather than to the farmer, can enhance loan provision and increase technology adoption (Farrin and Miranda 2014; Miranda and Gonzalez-Vega 2010). Likewise, the lower likelihood of default may encourage the smallholders to seek credit that they otherwise could not have risked taking. In this regard, the objective of this paper is to investigate the comparative impacts of the availability of micro-level and meso-level index-based rainfall insurance coupled loans (hereon referred to as insured loans) on the demand and supply side of the credit market. Here, micro-level insurance refers to loans where farmer groups are policy holders, while meso-level refers to loans where lending banks are the policy holders.

Using meso-level and micro-level insured loans as treatment, we investigate the impacts of access to such loans on demand side, i.e. farmer's decision to apply for the loan, and supply side, i.e. loan approval by the banks in northern Ghana. In order to do so, we conducted a randomized control trial (RCT) in northern Ghana to analyze the impact of insured loans on credit market access. Furthermore, we investigate if there are any differential impacts of insured loans on female versus male farmers. By providing payouts in times of drought, insurance may serve as a form of collateral, compensating for the relatively low levels of collateral held by female farmers or their higher risk aversion compared to male farmers. To the best of our knowledge, this study is the first to empirically investigate the impacts of insured loans on access to credit by gender of the farmers and varying insurance products.

Our empirical analysis uses panel data difference in difference models, which we estimate in three phases. First, we employ linear probability models to estimate the impact of insured loans on loan application and approval rates for all farmers. Second, we use Heckman selection model to account for the selection issue such that only those farmers that apply for loans can be in the approval pool from the banks. Third, we replicate the earlier methods to investigate the application and approval probabilities for male and female farmers separately. We find the following: (i) There is no impact of insured loans on farmer's loan application probabilities. This is not surprising since our sample is composed of bank clients who have been applying for loans for years with the application rates being as high as 90% in the pretreatment year. (ii) Banks are more likely to approve farmers in the presence of insured loans, specifically for the case of meso-level insurance when the banks are the policy holders. (iii) The increase in approval probabilities for both female and male farmers are quantitatively similar, however, it is moderately significant for female farmers and highly significant for male farmers.

These results have important policy implications. First, they imply that a properly designed index insurance product can lessen credit constraint by encouraging the lenders to increase their portfolio, i.e. the likelihood of loan approval to smallholder farmers. Second, such increase in loan receipts from the farmers can increase technology adoption by the farmers, thus increasing agricultural productivity and hence increasing overall welfare of smallholder farmers.

The remainder of the paper is structured as follows. Section 2 provides institutional context and state of agriculture in Ghana. Section 3 discusses theoretical framework and hypothesis testing. Section 4 presents methodology and data. Section 5 provides the results and Section 6 concludes.

2. BACKGROUND

The agricultural sector contributes to 30% of the Ghanaian GDP, employing more than half of the workforce (Ministry of Food and Agriculture (MOFA) 2006). In particular, 65% of the female headed households and 44% of male headed households are farming households. Most of the Ghanaian agriculture is based on smallholder farming (FAO 2012) and is mainly dominated by traditional farming practices (MOFA 2011). Agricultural production is primarily dependent on rainfall and soil quality with limited access to credit. The primary sources of credit are non-governmental organizations and a network of Rural and Community Banks (RCBs). There are 16 RCBs in the three northern regions, Northern, Upper East, and Upper West. The RCBs primarily provide loans to farmers in groups, which are formed by farmer themselves facilitated often by MOFA. The group formation helps farmers substitute collateral requirement by each other’s trust. Access to agricultural insurance, especially in the northern regions is extremely limited with only one licensed insurer in the country, Ghana Agricultural Insurance Pool (GAIP).

3. LITERATURE AND THEORETIAL FRAMEWORK

Seventy eight percent of the world’s poor live in rural areas and earn their livelihood from agricultural sector (World Bank 2008). This indicates that one of the most effective ways to reduce poverty is to improve agricultural efficiencies. This is particularly important for Sub-Saharan Africa (SSA), where agriculture is a major source of employment and contributes significant portion of the national economy (Bourdillon et al., 2002; Mendola, 2007; Kijima et al., 2008; Kassie et al., 2011). Particularly for Ghana, agriculture is a critical sector of the economy, contributing about 40% of the Gross Domestic Product and employing 60% of the labor force (Breisinger et al. 2011). This mismatch in employment and contribution indicates a comparatively low productivity of labor in agriculture. One of the main causes of this inefficiency is the low rates of adoption of improved production technologies and retention in the adoption of those technologies (Tripp and Rohrbach 2001; Feder, Just, and Zilberman 1985; Sunding and Zilberman 2001; Doss 2006). For example, an average farmer in SSA uses only about 8 kg of fertilizer per hectare, compared to 101 kg per hectare in South Asia and over 145 kg per hectare in the developed world (Morris et al. 2007). Therefore, increasing agricultural efficiencies through modern agricultural technology adoption could improve rural household well-being.

Low rates of technology adoption comes due to numerous barriers that hinder the adoption for the poor rural farmer in developing countries. Studies have found that heterogeneity in farmer's gender, education, soil quality, agro-climatic conditions, manure use, hiring of labor and extension services, cost and availability of seeds, credit constrains, informational barriers, and lack of effective commitment devices are the determinants of technology use (Ouma et al. 2002; Schultz 1963; Makokha et al. 2001; Conley and Udry 2010; Duflo, Kremer, and Robinson 2008; Foster and Rosenzweig 1995). Furthermore, credit constraint has been cited as the key bottleneck for technology adoption among various barriers to adoption (Croppenstedt, Demeke, and Meschi 2003; Salasya et al. 1998). Smallholder farmers lack access to credit either from the demand side due to risk of losing their assets pledged as collateral or from supply side due to lack of collateral.

There exist informal, non-market mechanisms among rural households in developing countries to ensure themselves against risk (Townsend 1994). However, such mechanisms can fail when the risk is systematic (i.e. rainfall or drought) rather than idiosyncratic, providing limited protection against such shocks to agricultural households. Furthermore, the lack of consumption smoothing mechanisms trap some agricultural households in low-risk, low-return agriculture as production risks impede the adoption of more profitable modern agricultural technologies such as fertilizer and hybrid seeds. This is particularly true for female headed households due to their lack of access and ownership of agricultural resources, ways to ensure themselves against systematic shocks, and credit constraints (Gladwin 1992; Khandker 1998; Quisumbing and Pandolfelli 2010).

Furthermore, these factors could potentially create a supply side barrier where lending institutions are more cautious to lend to female farmers due to lack of collateral among them. In this regard, mechanisms that remove the downside risks of adoption, such as insurance, may fundamentally encourage adoption among female headed households.

Theoretical modeling has shown that index insurance, especially at the meso-level (e.g., micro-finance institutions, farmers' cooperatives, input suppliers), where the indemnity goes to the risk aggregator rather than to the farmer, can enhance loan provision and subsequently increase technology adoption (Farrin and Miranda 2014; Miranda and Gonzalez-Vega 2010). Likewise, the lower likelihood of default may encourage the smallholders to seek credits that they otherwise could not have risked taking. In this regard, our paper focuses on two interrelated factors that have been identified as critical impediments to wider adoption of improved technologies in developing countries: lack of access to credit and the riskiness of agricultural returns, primarily due to significant rainfall variation. The objective of this paper is to investigate the comparative impacts of two kinds of treatments, i.e. availability of micro-level and meso-level drought insurance coupled loans (hereon referred to as insured loans), on demand and supply side credit market. Here, micro-level insurance refers to loans where farmer groups are policy holders, while meso-level refers to loans where the lending banks are the policy holders.

We particularly test the following hypotheses pertaining to credit access among smallholders from both supply and demand sides:

(1) Insured loans can reduce the borrower's exposure to the risk of loan defaults due to agricultural loss from irregular rainfall patterns, thereby encouraging the borrowers to seek credit, especially for those farmers that have micro-level insurance.
(2) Insured loans can reduce the lender's exposure to the risk of widespread loan defaults due to agricultural loss from irregular rainfall patterns, thereby encouraging the lenders to increase their credit portfolio for those farmers that have meso-level insurance.
(3) Since female farmers have lower collateral and are more sensitive to loan defaults than male farmers, female farmers will see a larger positive affect in both their likelihood of application and approval rates.

4. METHODOLOGY AND DATA

We conducted a randomized control trial (RCT) in northern Ghana to analyze the impact of insured loans on credit market access. First, we conducted a preliminary field visit in November 2014 with the local rural and community banks (RCBs) and some of their farmer group clients. In addition, we obtained a list of farmer groups that were clients of the fourteen RCBs from the Northern, Upper East and Upper West regions for agricultural loans. The datasheet contained information on total number of group members by gender, community location, loan size, two primary crops farmed, and acreage planted. Then we prepared our sample frame based on the following five criteria:

(i) Farmer groups that have been in good standing with the bank in terms of borrowing, potential groups that are qualified to receive loans, and groups that have been denied loan due to low regional rainfall.

(ii) Farmers that belong to districts that belong to low rainfall areas (between 800-1100mm annually) since the impact of insured loan is more likely to be seen when rainfall is low.

(iii) Farmer groups whose primary or secondary crop is maize since maize is the primary crop grown in the northern regions.

(iv) Farmer groups with 7-15 members due to budget constraints and logistics of maintaining smoother field work.

(v) Farmers that take out a loan of less than 10,000 GHC because farmers above this range are outliers and are beyond the definition of smallholder farmers.

This process resulted in a preliminary sample of 258 farmer groups, roughly representing 2500 farmers. Among all the farmer groups, Northern region comprises of five districts and 89 farmer groups, Upper West of ten districts and 33 farmer groups, and Upper East of six districts and 157 groups.

In February of 2015, we conducted a baseline survey of the 258 farmer groups. Figure 1 presents number of farmer groups per district in the northern regions. Then, we followed Giné and Yang (2009) and randomly divided our farmer groups into three roughly equal categories. Since the farmer groups are vastly different across the three northern regions and across their previous loan status (i.e. whether they were a loan borrower in the previous period or not), we stratified our sample to guarantee balance across these variables. In particular, balancing on borrower status is critical to our research question because we want to explore whether or not the treatments increase access to loans for groups that have not had access in the past. Randomizing treatments and control at the farmer group level rather than at the individual farmer level is preferred in our case as it serves to mitigate concerns about fairness which may arise when farmers in the same group are assigned to different treatments, with one treatment requiring insurance indemnities go to the lender while the other one does not (Giné and Yang 2009). Farmer groups in Category 1 serve as the Control, those in Category 2 serve as Treatment 1, and farmer groups in Category 3 serve as Treatment 2. For the control category, the invitation was for a standard loan, for the Treatment 1 category, the invitation was for an insured loan with farmers as policy holders, and for Treatment 2 category, the invitation was for an insured loan with the bank as the policy holder. For both treatments, the insurance premium is covered in full by the project (as in Karlan et al. 2011). The categories are further summarized below:

1. Control: No index insurance. Smallholders are offered conventional loans, but not index insurance, and lender does not employ index insurance to manage index insurance directly.
2. Treatment 1: Loans offered with mandatory index insurance, with indemnities assigned to smallholder.
3. Treatment 2: Loans offered with mandatory index insurance, with indemnities assigned to lender.

Table 1 contains number of farmer groups within each region by treatment categories. We list number of individual farmers in parenthesis. After randomization, we checked balance of the treatment and control categories by conducting mean comparison t-tests via oneway ANOVA and KWallis methods for several variables identified in the literature.[2]

[2] The variables of interest are: of interest: Total Production of Maize, Maize Fertilizer Input Quantity, Fertilizer Use Dummy, Hybrid/Certified Seed Use Dummy, Number of Loans Received Last Year, Received Agricultural Loan Last Year Dummy, Size of Agricultural Loan Last Year, On Time Repayment Dummy, Access to inputs, Number of Household Members, Total income, Agricultural Income, Perception of Last Growing Season, Risk Aversion, Acres Cultivated with Maize, Informal Risk Management Dummy, Number of Group Members, Preference for Cash or Cashless Loan, Total Land Size, and Remittance.

Table 2 contains descriptive statistics of covariates used in regression analysis. The average number of plots owned by farmers in northern Ghana is three. The average age of farmers is 45 years and they perceive two of the last five seasons as good seasons. Seventy three percent of the farmers have borrowed in the year before 2014 and forty seven percent of the farmers are females. Table 3 presents mean ttest comparison of wealth (asset) variables for male and female farmers. With an exception of savings, female farmers have significantly lower number of cattle, poultry, livestock, agricultural income and total acres planted.[3] Additionally, the mean ttest comparisons in Table 4 shows that the means of loan application for Treatment 1 is significantly higher than the control category for both all and new applicants (Panel A). However, we note that because the sample frame is taken from the banks, the application rate in the baseline year is over 90%. For the approval variable, both treatments 1 and 2 have significantly higher means for all applicants whereas only Treatment 1 is significant for new applicants (Panel B).

Table 5 further disaggregates the mean ttest comparisons for female and male farmers. For application variable, Treatment 1 has a significantly higher mean for female applicants, whereas Treatment 2 category has significantly higher means for male applicants (Panel A). For loan approval variable, both treatments 1 and 2 categories have significantly higher means for female applicants, whereas only Treatment 2 has significantly higher means for male applicants.

Our empirical analysis uses two types of estimation models under panel data differences-in-differences (DID) estimation methods. First, we use the linear probability model for our application binary variable. More explicitly, the relationships is modelled as the following:

$$Y_{ist} = \alpha_0 + \alpha_1 * T_{is} + \alpha_2 * R_t + \alpha_3 * T_s * R_t + \alpha_3 * X_{it} + \varepsilon_{ist} \quad (1)$$

Here, Y_{ist} takes 1 for those farmers that applied for agricultural loans and 0 for those who did not. T is a vector of 0 for control category, 1 for Treatment 1 category, and 2 for Treatment 2 category. R is a dummy, which is equal to 1 if the observation is from 2015 (i.e. post treatment). X_{it} is a set of control variables such as bank dummies, farmer's gender, age, number of plots owned, remittance, saving, number of good seasons in past five seasons, and number of people that can

[3] Since these farmers are bank clients, one of the prerequisites for them to be eligible for the agricultural loan is to open a Savings Account with the bank and deposit a certain percent of their loan amount as savings, which is likely the reason why savings is insignificant across male and female farmers.

help in the event of a draught. α_3 is the DID estimator, which measures the treatment impacts on likelihood of loan application. Second, we use Heckman Twostep Selection Model for our second outcome variable, approval from the banks. This is because our binary variable, loan application, suffers from self-selection bias such that approval data can be observed only for those farmers that applied for loans. There could be two reasons for why farmers may not apply for loans. A farmer may not apply for loans because she has enough income source to invest in farming. In contrast, a farmer may not apply for loans because she lacks the minimum collateral to do so and hence cannot risk entering the credit market. In such cases, the loan approval rates of those that have not applied for loans do not represent the loan approval rates of those that have not applied. Therefore, we follow Heckman (1979) and estimate our estimates for approval variable in two steps such as:

Step 1:

$$Y_{1ist} = \theta_0 + \theta_1 * T_{is} + \theta_2 * R_t + \theta_3 * T_s * R_t + \theta_4 * Risk_{is} + \theta_5 * X_{it} + \eta_{ist} \qquad (2)$$

Here, risk is the exclusion restriction such that farmers who are risk averse may not want to apply for the agricultural loans thinking that they might lose their collateral or social trust in case of a bad event. However, the banks are unable to observe the farmer's risk aversion and therefore, we calculate $\lambda_{i,}$, the inverse Mill's ratio. It is a monotone decreasing function of the probability that an observation is selected into the sample. We then include this probability into the second step (see Heckman (1979) for details).

Step 2:

$$Y_{2ist} = \delta_0 + \delta_1 * T_{is} + \delta_2 * R_t + \delta_3 * T_s * R_t + \delta_4 * \lambda_{is} + \delta_5 * X_{it} + \zeta_{ist} \qquad (3)$$

Y_{2ist} takes 1 for those farmers that have been approved for loans and 0 for those who have not. Therefore, after accounting for the selection, δ_3 is the DID estimator, which measures unbiased treatment impacts on likelihood of loan approval.

5. EMPIRICAL ANALYSIS AND RESULTS

To investigate the impact of treatment on credit access, we estimate several variants of panel data DID model, which we group in three phases. Phase one employs the linear probability model for all and new applicants as in Equation (1). Phase two employs Heckman twostep model in order to account for the selection issue as in Equations (2) and (3), and phase three investigates the treatment impacts across female and male farmers. In order to progressively build robust results, the estimations within each phase control for bank level heterogeneity, other characteristics of the farmer and the household and account for endogeneity. Subsection 5.1 presents analyses based on the Linear Probability Model and 5.2 on Heckman twostep, followed by a short discussion comparing results from these methods. Section 5.3 presents gender disaggregated estimations, followed by discussion and comparison of results across gender and with those from earlier sections. Finally, we draw some inferences based on the hypotheses presented in Section 3.

5.1 Treatment Impacts on Loan Application and Approval for All and New Applicants

The Linear Probability estimates of the treatment impacts estimated using Equation (1) are presented in Table 6. Panel A presents results for loan application binary variable and Panel B for loan approval binary variable. The first three columns present estimates for all applicants (Models 1-3) and last three columns present estimates for new applicants (Models 4-6). We estimate Models 1 and 4 without any controls. These models follow strict parallel assumption of DID model and does not include any controls. Models 2 and 5 control for bank level heterogeneity by including interaction terms for eleven RCBs and round. The rest of the three RCBs had a very low number of observations and could not be included in the controls. Model 3 and 6 include additional controls for age and gender of the farmer, number of plots owned, remittance, saving, number of good seasons in past five seasons, and number of people that can help in the event of a draught.

For the loan application variable, the models for all applicants give positive coefficients, however, they are not significant for any of the treatments (Panel A). The results are parallel for the new applicants with no statistical significance for any of the models (Models 4-6).

[Insert Table 6 here]

For loan approval binary variable, Treatment 1 (i.e. the farmer group is the policy holder) is statistically insignificant for all models including all and new applicants (Panel B, Models 1-6). However, for Treatment 2 (i.e. the bank is the policy holder) gives consistently positive and highly significant probabilities for all applicants indicating that availability of Treatment 2 increased the likelihood of loan approval for farmers (Panel B, Models 1-3). However, when we move to the sample pool of new applicants, these results become statistically insignificant (Models 4-6). We will not discuss the magnitudes of these effects as this model assumes no sample selection for the approval variable, which is a strong assumption given that only those farmers who applied for loans are in the approval sample pool.

Using several variants of the Linear Probability model, we find that insured loans do not increase the likelihood of farmer's loan application. This result is not that surprising given that we took our sample frame from the banks with over 90% of application rates in the baseline period. As discussed in Section 4, our model for loan approval variable may suffer from a selection problem because only those farmers that applied for agricultural loans are in the sample pool of loan approval so in the second phase of estimation, we use Heckman Twostep estimation.

5.2 Treatment Impacts on Loan Approval for All and New Applicants Using Heckman Model

As discussed in Section 4, using Linear Probability Model for loan approval binary variable without accounting for sample selection results into bias results due to nonrandomly selected samples (Heckman 1979). Therefore, we employ Heckman Twostep Model for estimations in this phase with farmer's risk aversion as the exclusion restriction for the first step of estimation. The empirical estimation is based on Equations (2) and (3), and we conduct two sets of estimations steps. Following the same procedure as in Subsection 5.1, we control for bank heterogeneity in Models 1 and 3 for all and new applicants, respectively, and employ additional controls in Models 2 and 3 for all and new applicants, respectively. The results are presented in Table 7.

[Insert Table 7 here]

For both all and new applicants, Treatment 1 impacts are statistically insignificant. This indicates that when the insurance is at the farmer group level, i.e. the payout goes to them in case of a trigger, it does not increase the bank's likelihood of farmer's loan approval. However, for all applicants for Treatment 2 when the bank is the policy holder, i.e. the payout goes directly to the banks, this increases the bank's likelihood of approving the farmer's loan. Both Models 1 and 2 show that Treatment 2 increases the probability of farmer's loan approval by 23%.[4] The probabilities for new applicants are statistically insignificant (Models 3-4).

Comparing the Linear Probability estimates to the Heckman Twostep, we find that controlling for selection leads to the results being significant at 5% as opposed to 1% in the LPM. Assuming that Heckman Twostep is a better estimation procedure, we conclude that Treatment 2 significantly

[4] We checked the robustness of these results by employing clustered bootstrapping for the standard errors. The results showed that Treatment 2 significantly increased the likelihood of farmer's loan approval by over 20%. These estimations could not be performed for the new samples or for the gender disaggregated sample because of the low sample size.

increases the likelihood of farmer's loan approval. In the next subsection, we discuss the treatment impacts by gender of the farmer.

5.3 Treatment Impacts by Gender of the Farmer

The objective of this estimation phase is to explore if there are any differential treatment impacts on loan application and approval rates between male and female farmers. We follow Subsections 5.1 and 5.2 and use Linear Probability and Heckman Twostep Models to separately investigate the treatment impacts. However, due to limitation in sample size and statistical insignificance earlier, we drop the analysis for new applicants for this phase. We present the analyses of results from LPM and Heckman Models in Subsections 5.3.1 and 5.3.2, respectively.

5.3.1 Treatment Impacts for Female and Male Farmers from Linear Probability Model

The LPM estimates of the treatment impacts for female and male farmers are presented in Table 8. Panel A presents results for the loan application variable and Panel B for the loan approval variable. Parallel to Subsection 5.2, Model 1 controls for bank heterogeneity and Model 2 employs additional controls. For the loan application variable, both treatments are statistically insignificant for both female and male applicants (Panel A). As discussed earlier, this is due to the fact that application rates were over 90% in the baseline period (94% for females and 89% for males). For the loan approval variable, Treatment 1 is insignificant for both male and female applicants. Parallel to earlier findings, these results indicate that Treatment 1 (i.e. when the farmer groups are the policy holder) does not increase bank's likelihood of farmer's loan approvals. In contrast, Treatment 2 has significantly positive impact on both female and male likelihood of loan approval (Panel B). Because we have not accounted for selection issue, we will not discuss the magnitude of these effects in this subsection.

[Insert Table 8 here]

Using several variants of LPM, we find that treatment impacts are statistically insignificant for the loan application variable for both female and male farmers. For the loan approval variable, we find that Treatment 2 significantly increases the likelihood of loan approval for both female and male applicants. We are cautious of these results at this stage since we have not accounted for selection issue. Therefore, we follow next with estimation results from Heckman Twostep Selection models for female and male farmers for the loan approval variable.

5.3.2 *Treatment Impacts for Female and Male Farmers from Heckman Model*

The Heckman Twostep estimates of the treatment impacts for female and male farmers are presented in Table 9. The estimation procedures for all four models presented in table follow those of Subsection 5.3.1.

[Insert Table 9 about here]

Parallel to our earlier findings in 5.3.1, we find that Treatment 1 impacts, although positive, are statistically insignificant for both female and male applicants. For Treatment 2, we find that the impacts are marginally and moderately significant for female and male farmers, respectively. Insured loans when the banks are the policy holder increases the likelihood of loan approval rates for female farmers by 24%. Similarly, Treatment 2 increases the likelihood of bank's loan approval by 24% for the male farmers. Accounting for selection issue, we find that Treatment 2 significantly increases the likelihood of loan approval for both female and male famers by the banks. Comparing these estimates with LPM, we find that the coefficient on Treatment 2 for female farmers are quantitatively robust but marginally significant. The results for the male farmers with Heckman Model are significant at 5% as opposed to 1% with the LPM.

The results obtained from the first phase of the estimation for loan approval reject our earlier hypotheses in Section 3. We had assumed that insured loans would encourage the borrowers to seek credit, especially for those farmers that have micro-level insurance. Although the coefficients for Treatment 1 were positive, we did not see any significant increase in the likelihood of loan application on either all, new or gender disaggregated samples. We speculate that these results behave such because we had a very high rate of loan application in the baseline, pretreatment period. The results obtained in phase two confirm our second hypothesis that insured loans can encourage the lenders to increase their credit portfolio for those farmers that have meso-level insurance by reducing lender's exposure to the risk of widespread loan defaults due to agricultural loss from irregular rainfall patterns. Finally, the results obtained in phase three reject the hypothesis that since female farmers have lower collateral and are more sensitive to loan defaults than male farmers, female farmers will see a larger positive affect in both their likelihood of application and approval rates. As stated earlier, loan application rates are very high for our baseline period hence producing an insignificant effect for application for both male and female farmers. When it comes to approval, both female and male applicants see significant increase in their likelihood of loan approval in Treatment 2 category with male farmers being more significant than female farmers. This result is in contrast to what we expected. A qualitative discussion with banks indicated that female farmers are more trustworthy and they are more likely to pay back loans as opposed to male farmers. Therefore, while injection of insured loans with the banks being the policy holder significantly increased the likelihood of female applicants' loan approval, it also significantly increased the likelihood of approval for the male farmers who are otherwise more risky clients.

6. CONCLUSION AND POLICY IMPLICATIONS

Food demand is projected to increase over the next fifteen years with around 60% in SSA and 30% in South Asia (World Bank 2016). This is a critical issue since SSA has the highest prevalence of food insecurity and is experiencing decreasing agricultural outputs over the last decade (Suri 2011). Therefore, barriers to technology adoption such as credit constraint that cause inefficiencies in production in this region are a natural problem that needs immediate attention. Furthermore, women farmers are considered the majority of the credit constraint population due to their lack of collateral. Hence, in this paper, we conducted a randomized control trial of drought index insurance with two types of insurance. In Treatment 1 category, loans offered to the farmer groups came with lumped index insurance, with indemnities assigned to farmer groups. In Treatment 2 category, loans were also offered with lumped index insurance but banks are the policy holders. Finally, in control category, farmer groups are provided with regular agricultural loans with no index insurance.

Through this paper, we aim to contribute to the limited literature on empirical findings of the impact of insured loans at the micro and meso-levels on credit application and approval rates. More specifically, our study is the first to estimate the impacts across female and male farmers to the best of our knowledge. We motivate our empirical analyses with a simple panel data DID linear probability model. Using several econometric techniques, we find that although the availability of insurance does not have significant impact on loan application, it significantly increases the likelihood of loan approval. In particular, Treatment 2 (meso-level insurance), where the bank is the policy holder, significantly increased the bank's loan approval rates across both female and male farmers. These findings contrast our hypothesis to some extent such that we had expected the loan application rates to increase but we found no significant impact due to the fact that our sample pool is existing bank clients who have over 90% application rates in the baseline period. Moreover, we had expected loan approvals to increase significantly more for female farmers as they have lower access to endowment. However, there are no significant differences in approval rates for male and female farmers, which we speculate due to two reasons. First, farmers obtain loans in groups, where group network serves as a collateral so the unavailability of collateral may not play a significant role in their approval rates compared to male farmers. Second, in our group discussions with the banks, they stated that female famers are more trustworthy since their payback is higher than male farmers with very low default rates. This implies that the availability of meso-level insurance pushed the banks to increase the likelihood of approval rates for male farmers (who were otherwise perceived as risky clients) more than it did for female farmers. These reasons when combined result in a win-win situation where supply side constraint is mitigated for both female and male farmers.

The results obtained in this study have important policy implications. Treatment 2 produces significantly positive impacts on loan approval rates for both female and male farmers and since credit and insurance constraints are common issues among rural farmers across the world, this approach of preventative facility in the form of insurance can reduce supply side barriers. In addition, our sample frame was active bank clients with over 90% application rates so for a population with lower application rates, availability of insurance could most likely increase loan application rates as well. Finally, when banks are more likely to approve a larger loan applicant pool, this increases the bank portfolio and decreases their risk and eventually may reduce the interest rate on agricultural loans. These circumstances could encourage both female and male farmers to adopt technology and reap the benefits of modern farming. The increased efficiency of agricultural productivity overall may mitigate the increasing food demand in SSA and elsewhere.

FIGURES AND TABLES

Figure 1: Map of Sample by District in Northern Ghana

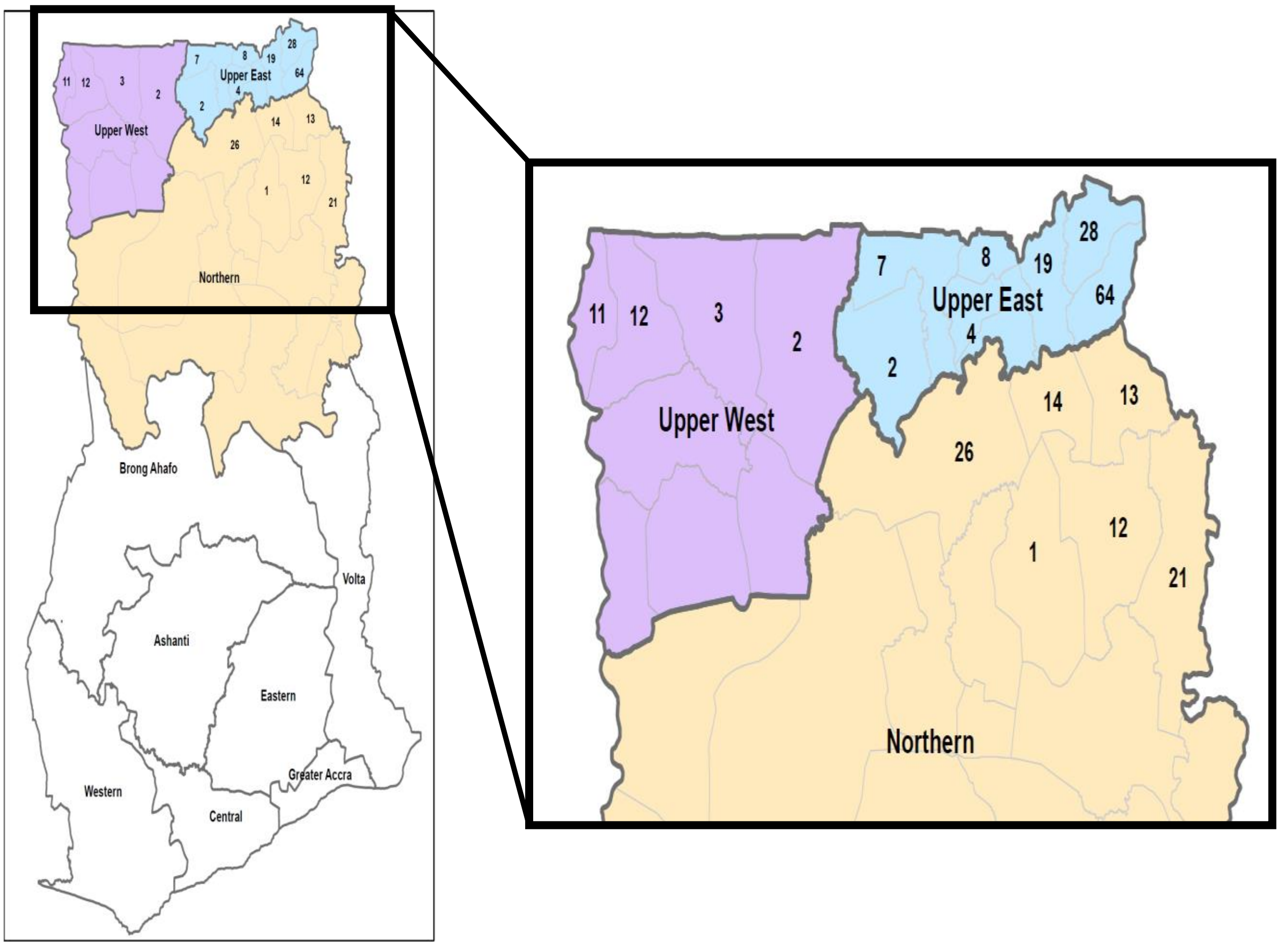

Table 1: Farmer groups by treatment categories and Stratification variables (borrower status and region)

Treatment Status	**Control**	**Treatment 1**	**Treatment 2**	**Total**
Non-Borrower	11	12	12	35
	(34)	(36)	(36)	(106)
Borrower	22	20	21	63
	(67)	(60)	(67)	(194)
Northern Region	33	32	33	98
	(101)	(96)	(103)	(300)
Non-Borrower	7	9	8	24
	(21)	(27)	(24)	(72)
Borrower	37	35	36	108
	(111)	(105)	(108)	(324)
Upper East Region	44	44	44	132
	(132)	(132)	(132)	(396)
Non-Borrower	4	3	3	10
	(12)	(9)	(9)	(30)
Borrower	5	8	5	18
	(15)	(24)	(15)	(54)
Upper West Region	9	11	8	28
	(27)	(33)	(24)	(84)
Total	87	88	87	258
	(260)	(261)	(259)	(780)

Note: Individual farmer level data are given in parentheses.

Table 2: Descriptive statistics of covariates used in the regression analyses

Variable	Sample Mean	Std. Dev.
Number of plots owned	3.00	1.05
Remittance (GHC)	101.67	205.16
Log of Saving	0.68	0.47
Age of the respondent	45.97	13.18
Number of last 5 good seasons	2.37	.92
Number of help in case of draught	1.43	3.07
	Sample Proportion	Std. Err.
Risk Aversion		
1. Very willing to take risk	0.32	0.02
2. Willing to take risk	0.39	0.02
3. Indifferent to taking risk	0.12	0.01
4. Not willing to take risk	0.15	0.01
5. Not at all willing to take risk	0.01	0.00
Loan status in the past year 2014		
Non-Borrower	0.27	0.02
Borrower	0.73	0.02
Gender of the respondent		
Male	0.53	0.02
Female	0.47	0.02

Table 3: Pairwise Mean Comparisons for Males and Females

	Males	Females	
Cattle	5.7	3.1	**
Poultry	26	20.4	***
Small Livestock	13.6	10.8	*
Total Income	2403.6	1973.8	***
Agricultural Income	1531	1278	***
Savings Account	0.66	0.7	
Amount of Savings	368.3	352	
Total Acres Planted	7.8	5.7	***

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

Table 4: Pairwise Mean Comparisons for All and New Applicants

Variables	Control	Treatment1		Treatment2	
PANEL A – LOAN APPLICATION PROBABILITIES					
Loan Application All Round 0	0.9037	0.9403		0.9	
Loan Application All Round 1	0.7665	0.8506	**	0.7915	
Loan Application New Round 0	0.7818	0.8125		0.75	***
Loan Application New Round 1	0.6719	0.8333	**	0.7826	
PANEL B - LOAN APPROVAL PROBABILITIES					
Loan Approval All Round 0	0.7423	0.7791		0.6718	*
Loan Approval All Round 1	0.6650	0.8219	***	0.8413	***
Loan Approval New Round 0	0.0448	0.2174	***	0	
Loan Approval New Round 1	0.4565	0.7	**	0.4737	

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

Table 5: Pairwise Mean Comparisons for Male and Female Applicants

	Control	Treatment1		Treatment2	
PANEL A – LOAN APPLICATTION PROBABILITIES					
Female Applicants Round 0	0.9381	0.9722		0.973	
Female Applicants Round 1	0.7321	0.8636	***	0.8195	
Male Applicants Round 0	0.8760	0.9032		0.8181	**
Male Applicants Round 0	0.7931	0.8372		0.7619	***
PANEL B – LOAN APPROVAL PROBABILITIES					
Female Approvals Round 0	0.7232	0.7954		0.7218	
Female Approvals Round 1	0.6136	0.8649	***	0.8349	***
Male Approvals Round 0	0.7568	0.7619		0.6190	**
Male Approvals Round 1	0.7043	0.7778		0.8485	**

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

Table 6: Treatments Impacts on Loan Application and Approval Probability for All and New Applicants

	All Applicants			New Applicants		
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PANEL A – LOAN APPLICATION LINEAR PROBABILITY MODEL						
Treatment 1	0.0474	0.0421	0.0412	0.131	0.142	0.129
	(0.0719)	(0.0706)	(0.0701)	(0.177)	(0.167)	(0.163)
Treatment 2	0.0474	0.0310	0.0346	0.143	0.140	0.132
	(0.0719)	(0.0762)	(0.0759)	(0.191)	(0.170)	(0.168)
Observations	1,406	1,406	1,394	368	368	368
R-squared	0.031	0.098	0.112	0.016	0.179	0.221
PANEL B – LOAN APPROVAL LINEAR PROBABILITY MODEL						
Treatment 1	0.1128	0.0822	0.0987	0.0391	-0.1171	-0.1143
	(0.0896)	(0.0897)	(0.0871)	(0.1868)	(0.1454)	(0.1347)
Treatment 2	0.2218**	0.229***	0.232***	0.0295	0.0510	0.0613
	(0.0895)	(0.0875)	(0.0814)	(0.1939)	(0.0651)	(0.0636)
Observations	1,344	1,344	1,331	326	326	326
R-squared	0.017	0.109	0.160	0.317	0.727	0.741
Bank Dummies	No	Yes	Yes	No	Yes	Yes
Additional Controls	No	No	Yes	No	No	Yes

Standard errors are clustered at group level and are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Eleven out of fourteen banks have been included in the dummy, rest three had very low observations. Additional controls include number of plots owned by farmers, remittance, saving, number of good seasons in past 5 seasons, gender of the respondent, age, and number of people that can help in the event of a draught.

Table 7: Treatment Effects From Heckman Selection Model on Loan Approval Probability for All and New Applicants

	All Applicants		New Applicants	
VARIABLES	Model 1	Model 2	Model 3	Model 4
PANEL A – MANUAL TWO STEP ESTIMATES				
Treatment 1	0.154	0.146	-0.00853	-0.00699
	(0.103)	(0.101)	(0.0917)	(0.0959)
Treatment 2	0.231**	0.230**	0.0685	0.0699
	(0.0972)	(0.0948)	(0.0624)	(0.0658)
Mills Lambda	0.228	0.190	-0.00387	0.000582
	(0.269)	(0.228)	(0.0504)	(0.0513)
Observations	1,039	1,039	187	187
R-squared	0.099	0.121	0.870	0.870
Bank Dummies	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes
Exclusion Restriction	Risk Aversion Likert Scale 1-5			

Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Eleven out of fourteen banks have been included in the dummy, rest three had very low observations. Controls include number of plots owned by farmers, remittance, saving, number of good seasons in past 5 seasons, gender of the respondent, age, and number of people that can help in the event of a draught.

Table 8: Treatment Impacts from Linear Probability Models for Male and Female Applicants

	Female		Male	
VARIABLES	(1)	(2)	(1)	(2)
PANEL A – LOAN APPLICATION PROBABILITY				
Treatment 1	0.127	0.127	-0.0262	-0.0248
	(0.0881)	(0.0871)	(0.0861)	(0.0858)
Treatment 2	0.0937	0.0925	-0.0137	-0.00939
	(0.0928)	(0.0919)	(0.0972)	(0.0970)
Observations	662	661	744	733
R-squared	0.177	0.200	0.078	0.096
PANEL B – LOAN APPROVAL PROBABILITY				
Treatment 1	0.100	0.117	0.0764	0.0806
	(0.128)	(0.126)	(0.106)	(0.104)
Treatment 2	0.216*	0.215*	0.246**	0.249**
	(0.118)	(0.116)	(0.103)	(0.102)
Observations	638	637	706	694
R-squared	0.144	0.187	0.122	0.164
Bank Dummies	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1. Clustered robust standard errors in parentheses. Bank dummies include eleven out of fourteen banks, rest three had very low observations. Additional controls include, number of plots owned by farmers, remittance, saving, number of good seasons in past 5 seasons, gender of the respondent, age, and number of people that can help in the event of a draught.

Table 9: Treatment Impacts on Loan Approval Probability from Heckman Model

	Female		Male	
VARIABLES	(1)	(2)	(1)	(2)
Treatment 1	0.231	0.210	0.0821	0.0879
	(0.156)	(0.154)	(0.129)	(0.127)
Treatment 2	0.242*	0.241*	0.243**	0.245**
	(0.139)	(0.138)	(0.118)	(0.119)
Mills Lambda	0.267	0.126	0.743*	0.625**
	(0.223)	(0.206)	(0.428)	(0.315)
Observations	502	502	528	520
R-squared	0.119	0.142	0.123	0.131
Bank Dummies	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	No	Yes
Exclusion Restriction	Risk Aversion Likert Scale 1-5			

Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include number of plots owned by farmers, remittance, saving, number of good seasons in past 5 seasons, gender of the respondent, age, number of people that can help in the event of a draught. Model 1 is the Eleven out of fourteen banks have been included in the dummy, rest three had very low observations.

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