Gender and Credit Access: Evidence from Bundling Agricultural Insurance and Credit in Ghana

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Abstract.

Women farmers across the developing world lack access to agricultural resources. Multiple market failures impede high-return investments, primarily, inability to provide adequate collateral and high covariant risk associated with rain-fed agricultural production. These barriers could be reduced by integrating microfinance and index insurance into agricultural credit markets. In this regard, we examine two products: (i) Micro-insured loans where borrowers acquire a personal index insurance contract (bundled with loans) to which they are the beneficiary, and (ii) Meso-insured loans where borrowers acquire an index insurance contract (bundled with loans) but lender is the beneficiary. Our results indicate that both micro-insured loans and meso-insured loans boost the likelihood of loan received and loan approvals for female farmers but only meso-level insured loans increase loan approvals for male farmers. Our results have important policy implications, especially offering differentiated products to male and female farmers to expand credit access and related technology adoption.

Key words: gender, credit, insurance, Ghana, South Africa

1. Introduction

It is a well-known fact that agricultural productivity is low in Sub Saharan Africa due to low rates of adoption and retention of improved production technologies, such as improved seeds and fertilizer (Doss 2006; Feder, Just, and Zilberman 1985; Sunding and Zilberman 2001). The low rates of adoption are due to numerous barriers to adoption common across many developing countries, including, 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). Of these, poor access to credit and the riskiness of agricultural returns, primarily affect both farmers' demand and banks' supply of agricultural credit (Hertz 2009; Mude and Barrett 2012; Farrin and Miranda 2015).

In particular, the lower adoption rates among female farmers 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 et al., 2015). Female farmers tend to have a higher 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 et al., 2008; Fletschner et al., 2010; Gladwin, 1992; Khandker, 1998; Mishra & Sam, 2016; Quisumbing & Pandolfelli, 2010). 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 et al., 2008; Croson & 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 et al., 1995). Similarly, credit groups with higher percentages of females had significantly better repayment rates in Bangladesh and Guatemala (Kevane & Wydick, 2001; Sharma & Zeller, 1997). 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 index-insurance 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. An index-insurance 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, theoretically, index-insurance 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 index-insurance 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 index-insurance 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 proposed (Carter, Cheng, and Sarris 2011; Miranda and Gonzalez-Vega 2010). Theoretical models and experimental evidence have shown that such a product can reduce the risk of defaults and improve farmer's creditworthiness, credit sustainability, and technology adoption (Carter et al., 2011; Farrin & Miranda, 2015b; Miranda & Gonzalez-Vega, 2010; Mishra et al., 2021; Shoji, 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. However, to the best of our knowledge, there are no studies that explore the differential impacts of micro- and meso-insurance on credit access, disaggregated by gender.

In this regard, the objective of this paper is to investigate if there is heterogeneity in these impacts, especially for female farmers on the demand side (due to 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 uses a simple theoretical model and data from a randomized control trial (RCT) in northern Ghana and employs differences-in-difference and fixed effects models. We find that (i) there is a positive and statistically significant association for both micro- and meso-insured loans and the likelihood of loan received for female farmers; (ii) there is a positive and statistically significant association for meso-insured loans and the likelihood of loan received for both female and male farmers; and (iii) neither of the insurance has any association with loan application probability. The lack of significant results on loan application probability might be due to preexisting high levels of loan application rates of around 90% for female and male farmers. These findings indicate that index insurance might be more effective in reducing credit constraints and technology adoption among smallholder farmers when targeted on the supply side.[1] More specifically, for lenders, the insurance product design does not seem to matter for female farmers, due to their higher creditworthiness, but it does matter for male farmers; banks seem more confident to lend to males when the payouts go directly to the banks. 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

Agriculture sector contributes to around 19% of the GDP of the Ghanaian economy and employs more than half of the workforce in 2012 (Ghana Statistical Service, 2014). Of total farmers, around 30% are females and 70% are males (FAO 2012). The Ghanaian government has increased the share of total public expenditure to the food and agriculture sector from 2007 to 2013, but the sector's contribution to the economy has decreased during this period (Food and Agriculture Policy Decision Analysis 2015). According to the Ghanaian Ministry of Food and Agriculture (MOFA) (2011), these inefficiencies in the agricultural sector are a result of the high proportion of smallholder farmers using traditional, rainfall dependent production systems. For example, agricultural technologies such as inorganic fertilizer and certified seeds

[1] 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.

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 (C. R. Doss & Morris, 2000). Lack of access to credit is a primary reason for the low levels of adoption of improved production technologies (Nair & Fissha, 2010). As a result, the Ghanaian government created a publicly owned agricultural development bank with an agricultural lending requirement for smallholders (Nair & 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.[2] Once these farmer groups are formed, they are required to prepare a budget for agricultural inputs usually with the help of extension agents or other related non-governmental organizations to apply for loans.

In addition to credit constraints, climate change is another major factor affecting the Ghanaian agriculture. The changing climate imposes the highest risk on smallholder farmers whose livelihoods depend on agriculture. In this regard, 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.

3. Theoretical Model

In this section, we formalize the impacts of insured loans on farmers' loan application and approval rates by developing a simple theoretical model based on Giné and Yang (2009)'s. However, our model differs from theirs in four important ways. First, we 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 default penalty $\varphi \in [0, \infty)$, which can be defined as a social penalty (i.e., farmer's perception of shame from defaulting). Second, we explore separate impacts of micro- versus meso-level

[2] 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.

insured loans on credit access, with a special focus on gender by varying model parameters. Third, we consider these impacts from the lender's perspective in addition to the borrowers'.

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 $Y_T < pY_H + (1-p)Y_L$.[3] 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. 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, their consumption is Y_T and therefore their utility $U_T = u(Y_T)$. In contrast, if they decide to plant with improved technology, their consumption is given by:

[3] 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.

$$C_j = \begin{cases} \omega + Y_H - R - \kappa & j = H, high\ state \\ \omega + Y_L - \mathrm{C} - \kappa & j = L, low\ state \end{cases} \quad (1)$$

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

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

Suppose that banks offer a bundle of credit with drought 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. Since the knowledge of insurance payout is public, not making repayment imposes a social shame in this case. Whether the farmer will strategically default or not essentially depends on how the farmer values their social penalty φ. For the type of farmer, with lower value such that $R^I \geq \mathrm{C} + \varphi_L$ holds, they default and keep the insurance payout such that their consumption in a drought state is $\omega + Y_L + R^I - \mathrm{C} - \varphi_L - \kappa$. This implies an expected utility from a micro-insured loas (U_{MI}) as follows:

$$U_{MI} = P(Y_H, h)u(\omega + Y_H - R^I - \kappa) + P(Y_H, l)u(\omega + Y_H - \kappa) + P(Y_L, h)u(\omega + Y_L - \mathrm{C} - \kappa) \qquad (3)$$
$$+ P(Y_L, l)u\big(\omega + Y_L + R^I - \mathrm{C} - \varphi_L - \kappa\big)$$

Alternatively, for the type with higher value for φ such that $R^I < \mathrm{C} + \varphi_H$ holds, they repay such that the consumption in a drought state is $\omega + Y_L - \kappa$. Therefore, the expected utility U_{MI} can be expressed as:

$$U_{MI} = P(Y_H, h)u(\omega + Y_H - R^I - \kappa) + P(Y_H, l)u(\omega + Y_H - \kappa) + P(Y_L, h)u(\omega + Y_L - \mathrm{C} - \kappa) \qquad (4)$$
$$+ P(Y_L, l)u(\omega + Y_L - \kappa)$$

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 and not penalize the farmer. 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 not penalize the farmer in drought state. Thus, the expected utility of the farmer from a meso-insured loan, U_{ME}, can be expressed as:

$$U_{ME} = P(Y_H, h)u(\omega + Y_H - R^I - \kappa) + P(Y_H, l)u(\omega + Y_H - \kappa) + P(Y_L, h)u(\omega + Y_L - C - \kappa) \qquad (5)$$
$$+ [\tau(P(Y_L, l)u(\omega + Y_L - \kappa)) + (1 - \tau)P(Y_L, l)u(\omega + Y_L - C - \kappa)]$$

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 the farmer's loan 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, they 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:

$$u(\omega + Y_T) = P_U[pu(\omega + Y_H - R - \kappa) + (1-p)u(\omega + Y_L - C - \kappa)] + (1 - P_U)u(\omega + Y_T - \kappa) \tag{6}$$

For micro-insured case, we have two ICs, each for types φ_L and φ_H such that the IC between no application and micro-insured loan application for the former type can be defined as:

$$u(\omega + Y_T) = P_{MI}[P(Y_H, h)u(\omega + Y_H - R^I - \kappa) + P(Y_H, l)u(\omega + Y_H - \kappa) + P(Y_L, h)u(\omega + Y_L - C - \kappa) + P(Y_L, l)u\big(\omega + Y_L + R^I - C - \varphi_L - \kappa\big)] + (1 - P_{MI})u(\omega + Y_T - \kappa) \tag{7}$$

And for the latter type can be defined as:

$$u(\omega + Y_T) = P_{MI}[P(Y_H, h)u(\omega + Y_H - R^I - \kappa) + P(Y_H, l)u(\omega + Y_H - \kappa) + P(Y_L, h)u(\omega + Y_L - C - \kappa) + P(Y_L, l)u(\omega + Y_L - \kappa)] + (1 - P_{MI})u(\omega + Y_T - \kappa) \tag{8}$$

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

$$u(\omega + Y_T) = P_{ME}[P(Y_H, h)u(\omega + Y_H - R^I - \kappa) + P(Y_H, l)u(\omega + Y_H - \kappa) + P(Y_L, h)u(\omega + Y_L - C - \kappa) + [\tau(P(Y_L, l)u(\omega + Y_L - \kappa)) + (1-\tau)P(Y_L, l)u(\omega + Y_L - C - \kappa)] + (1 - P_{ME})u(\omega + Y_T - \kappa) \tag{9}$$

In order to draw the ICs, we plot a combination of the CRRA coefficient and mean preserving spread between the outcomes, i.e., $P * Y_H + (1-P) * Y_L = E(Y)$ such that the farmer is indifferent between applying for a loan to produce with improved versus traditional seeds.[4] Furthermore, to examine how predictions change over gender, we follow (Giné & Yang, 2009b) 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 $Y_H = (EY - (1-p) * Y_L)/p$ yield to ensure a mean preserving spread and traditional yield $Y_T = 5$. Furthermore, we assume a collateral value of $\mathrm{C} = 0.5$ and approval rates of $P_{ME} = 0.9 \geq P_{MI} = 0.8 \geq P_U = 0.7$ (See Table 1 for more detail).

[Insert Table 1]

In Table 2, we provide the changes in specifications of key parameters that we believe would drive the farmer application behavior by gender (Panel A), followed by simulated application rates for each loan type and case (Panel B). We also present the results graphically in Figure 1. 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 the RCT study.[5] By this we hope to gain a rough expectation regarding the impact of the insured loans on application rates.

[4] In addition, we follow Giné and Yang (2009) to plot a combination of the constant relative risk aversion (CRRA) coefficient and low outcome state yields Y_L and find similar results.
[5] In the RCT sample, the average application rate in the baseline is about 91%. In this sense, the predictions from impact of insured loans on application rates are around this rate.

[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-default (red curve) and Micro-no default (orange curve) are the ICs between applying for the micro-insured loan or not for the φ_L and φ_H type farmer, respectively. Similarly, Meso (green curve) and Uninsured (blue curve) are the ICs between applying or not for the meso-insured and uninsured loan, respectively. In general, micro- and meso-insured loans allow farmers with a high risk-aversion to apply for a loan. As the spread between high and low state yields increase, farmers with even higher risk aversions are willing to apply for loans, effectively increasing demand for the loans.

[Figure 1 here]

We speculate that insured loan application rates may differ by gender based on the evidenced differences in characteristics of females and males. We specifically consider four key differences between female and male simulation parameters and draw separate ICs for them. The literature has found that females value shame higher than males (O'Connor et al., 1994; Wright et al., 1989) so we assume $\varphi_L = 1 \; and \; 0.6$ for females and males, respectively. As discussed earlier, we assume a lower trust parameter for females than males, i.e., $\tau = 0.3 \; and \; 0.6$, respectively. 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.[6] To reflect this, we assume collateral values of $\mathrm{C} = 0.7 \; and \; 0.5$ 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

[6] 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.

due to the impossibility of strategic default in the latter case. Therefore, 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 are 98.9, 90.3, and 89.3% for micro-insured, meso-insured and uninsured loans, respectively. This implies that a higher proportion of females will apply for micro-insured loans than uninsured loans but they are almost indifferent between meso and uninsured loans. 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 99.1, 95.7, and 92.3% for micro-insured, meso-insured and uninsured loans, respectively. Therefore, we make the following testable prediction:

Proposition 1 – For female farmers, micro-and meso-insured loan application rates will be significantly and marginally higher than uninsured loans.

Proposition 2 – For male farmers, uninsured loan application rates will be marginally higher than micro-insured loan and almost indifferent to meso-insured 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:

$$\prod_U = pR + (1-p)\mathrm{C}' - (1+r')K \tag{10}$$

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:

$$\prod_{MI} = P(Y_H,h)\left(\frac{R}{q}\right) + P(Y_H,l)\left(\frac{R}{q}\right) + P(Y_L,l)\left[(1-\lambda)\left(\frac{R}{q}\right) + \lambda\mathrm{C}'\right] + P(Y_L,h)\mathrm{C}' - (1+r')(\pi + K) \tag{11}$$

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:

$$\prod_{ME} = P(Y_H,h)\left(\frac{R}{q}\right) + P(Y_H,l)\left(\frac{R}{q}\right) + P(Y_L,l)\left(\frac{R}{q}\right) + P(Y_L,h)\mathrm{C}' - (1+r')(\pi + K) \tag{12}$$

3.4 Model simulations for Credit Supply

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 A1).

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 et al., 2008; Croson &

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 2 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 proposition based on the model:

Proposition 3 – 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. Data and Descriptive Statistics

The data for this study comes from a randomized control trial project in northern Ghana. It consists 779 farmers from 258 farmer groups divided across the Northern, Upper East, and Upper West regions. Female farmers make up 47% of the sample.[7] The data is collected for three growing seasons across three years, baseline in 2015, follow-up 1 in 2016, and follow-up 2 in 2017. The main outcome variables are binary in nature, they are: (i) whether the farmers received the loan, they applied for the loan, and they were approved for the loan. There are two binary, primary determinant variables: (i) micro-insured loans and (ii) meso-insured loans. The traditional agricultural loan without drought index insurance is the base category. For more details on experiment design and data collection, please see Mishra et al. (2021).

[7] which is higher than the national representation of female farmers of 30%.

We present descriptive statistics of key variables, including mean t-test comparisons by gender, in Table 3.[8] Among proxies for financial access, we have information on whether households have savings with the bank, outstanding debt, previously borrowed. About 63% of the males and 72% of the females have some savings with the bank; this difference statistically significant at 1% level. Similarly, about 19% of the males and 21% of the females have outstanding debt with the bank, and 70% of the males and 77% of the females have previously borrowed from the bank; the latter is statistically significant at 5% level. 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 and less cattle than males, which is consistent with the literature.

The data also contains information on agricultural income, number of agricultural plots owned, cattle, and remittances as proxies for household wealth and assets. These variables show that males have higher household wealth and assets. Next, we have data on risk perception, risk aversion, and mechanisms to cope with risk. For either of these variables, we do not find any statistically significant difference across males and females. Here, risk aversion is self-reported using a five-point Likert scale for risk aversion from lowest to highest level of risks (Hardeweg et al., 2011). Lastly, female farmers tend to live in smaller size households compared to males.

[Insert Table 3 here]

Table 4 presents mean t-test comparisons of outcome variables of interest, loan received, loan application, and loan approval by insurance status for each survey round. These are presented first for females in Panel A and males in Panel B. In Panel A, we find no statistically significant difference for any of the outcome variables across the loans in the baseline. In follow-ups 1 and 2, we find some cases of

[8] A more general descriptive statistics can be found in Mishra et al. (2021).

higher rates of loans received, applied, and approved for meso-and micro-insured loans. In Panel B, the statistically significant differences are also scares but there is a notable pattern. For example, the rates of loan received, and approved are statistically higher in micro- and meso-insured loans in follow-ups 1 and 2. We also note that this sample has a very high baseline rate of loan application, about 88% and 95 % for males and females, respectively.

[Insert Table 4 here]

5. Empirical Model and Results

5.1 Empirical Model

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

$$Y_{it} = \alpha + \gamma M1 + \mu M2 + \lambda R_t + \theta(M1 * R_t) + \beta(M2 * R_t) + \delta X_{it} + \varepsilon_{it} \qquad (13)$$

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 received, loan application, and loan approval estimation models. $M1$ is one for the micro-insured loan and zero otherwise and $M2$ is one for f the meso-insured loan and zero otherwise. R_t is an indicator function representing each of the three rounds of survey. The parameters of interest are θ and β; they respectively measure the relationship between micro- and meso-insured loans and outcome variables. X_{it} is a vector of respondent characteristics that may impact the outcome variable. Since the data comes 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 had previously borrowed from the bank, bank dummy, and region dummy. 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.

5.2 Results and Discussion

We use equation 13 to separately estimate the relationship between insured loans and credit access parameters by gender. For model robustness, we also estimate our results using fixed effects model, followed by four more model specifications as follows: (i) combining the two follow-up rounds, (ii) farmer group level analysis with DID and Fixed effects (FE) models, and (iii) propensity score matching (PSM). The PSM estimations are done for loan approval variable because only those farmers that apply for loans can be approved for loans which implies that there is a sample selection at this stage. Therefore, the matching is done for each of the micro-insured and meso-insured loans separately based on key covariates.[9]

5.2.1 Insured Loans and Loan Received Outcome

We present the results of our DID and FE models for loan received outcome variable in Table 4 below.[10] The first column presents results for females, followed by males in the second column. This is followed by FE model results in the fourth and fifth columns for females and males, respectively. For females, we find that having micro-insured loans is associated with increased likelihood of receiving loans by over 21 percentage points in follow-up 1. Similarly, having meso-insured loans is associated with increased likelihood of receiving loans by over 20 percentage points. These results are statistically significant at 10% level, but for follow-up 2, we do not find statistically significant results. For males, we do not find any statistically significant results for micro-insured loans. However, for meso-insured loans, we find that there is a positive and significant association in that it increases the likelihood of receiving loans by over 23 percentage points in follow-up 1. These results are identical using fixed effects models. Comparing across gender, these results imply that while the insurance type does not matter for credit access for

[9] They are: previous borrowing experience, risk aversion, savings, outstanding debt, remittance income, cattle, perception of good season in the last five seasons, agricultural income, land owned, household size, respondent's education, preference for cash versus kind loan, help at the time of drought, respondent is the head of the house, region, and bank.

[10] Standard errors are clustered at the farmer group level in the DID model.

females, it does for males. Since the probability of receiving loan is comprised of the probability of applying for loan and being approved, we will unpack this further in the next two subsections.

[Insert Table 5 here]

5.2.2 *Insured Loans and Loan Application Outcome*

Table 6 presents DID and FE estimates loan application outcome variable; standard errors are clustered at farmer group level in the DID model. For females, with an exception of follow-up 2 for micro-insured loans, we find positive signs for the insured loan impacts ranging from about 8 to 13 percentage points for micro-insured loans and meso-insured loans. However, they are not statistically significant. These results do not align well with Proposition 1, which predicts that for females, micro-and meso-insured loan application rates will be marginally higher than uninsured loans. For males, the results similar but also statistically not significant. Therefore, these results do not fully align with proposition 2 which predicted that male farmers will be less likely to apply for micro-insured loans and indifferent for meso-insured loans compared to uninsured loans.

[Insert Table 6 here]

We speculate that 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. Regardless, it does seem that the demand side has no effect on credit access for either male or female farmers regardless of the insurance type.

5.2.3 Insured Loans and Loan Approval Outcome

Table 7 presents the DID and FE estimates of the insured loans on the loan approval variable, with standard errors clustered at farmer group level in the former models. For both male and female applicants, the estimated impacts of micro-insured loans on loan approval are positive but statistically not significant. For meso-insured loans, however, we find that the coefficients for females are between 24-25 percentage points and statistically significant in follow-up 1.[11] For males, we find that the coefficients of meso-insured loans are between 26 to 30 percentage points and statistically significant at 5% level.

[Insert Table 7 here]

These results partially confirm our Proposition 3 in that both females 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. Conversely, in the meso-insured loan type, banks will receive the payouts directly.

5.2.4 Robustness checks

In this subsection, we discuss results from our four additional model specifications as mentioned earlier: (i) combining the two follow-up rounds, (ii) farmer group level analysis with DID and Fixed effects (FE) models, and (iii) propensity score matching. These results are presented in the appendix section. First, in

[11] In follow-up 2, the statical significance only shows in the FE model at 10% for females.

the model where we combine the rounds, we find that while micro-insured loans have no statistically significant relationship with any of the three outcome variables, meso-insured loans are positively associated with higher likelihood of receiving loans and loan approval for both females and males (Table 9). The approval likelihoods are 16 versus 22 percentage points for female and males, respectively. Second, in the model where we run group level analysis with DID and FE models, we find that micro-insured loan is associated with a higher likelihood of receiving loan and loan approval for females between 19 to 25 and 33 percentage points, respectively (Table 9, Panel A). For males, we find that meso-insured loan is associated with increased likelihood of receiving loans and loan approval by 25 and 34 percentage points, respectively. The FE results are qualitatively similar in that micro-insured loans have positive association with the likelihood of loan received and loan approval for females whereas meso-insured loans have positive association with increased likelihood of loan received and loan approval for both females and males (Table 9, Panel B). The probabilities are slightly higher for males. Lastly, the results from propensity score matching for loan approval probabilities show that there is a positive association with micro-insured loans for females but no statistically meaningful relationship for males (Table 10). For meso-insured loans, there is a positive association for both females and females. These results are again qualitatively similar to earlier ones. Overall, these results indicate that access to credit for these smallholder farmers is positively associated with meso-insured loans. This is possibly because banks are more confident to approve loans for both females and males when they have the control over payouts as opposed to when the farmers do. This is particularly true for male borrowers.

6 Conclusion and Policy Implications

Climate-smart agriculture and food systems innovations is at the heart of discussions on climate change to build sustainable, equitable, and resilient food systems (US Department of Agriculture, 2023). Increasingly, women are at the heart of this issue because they are often responsible for growing food and deciding daily meals for the family. Therefore, any solutions to climate-related food production system should be designed per the gendered needs of the system. As such, this study utilizes a simple theoretical model and data from an RCT to examine the relationship between two types of insurance products and credit access outcomes (loan application, loan approval, and loan received) separately for male and female farmers. The first insurance product is an agricultural loan coupled with index insurance, with the contract assigned to the farmer groups (micro-insured loan). The second insurance product is also an agricultural loan coupled with index insurance, but with the contract assigned to the banks (meso-insured loan). Finally, they are measured against an agricultural loan without index insurance.

Using a difference-in-differences linear probability model and a fixed effects model, we find evidence that both micro-insured loans and meso-insured loans are associated with increased likelihood of both loan received and loan approval for female farmers. In contrast, only meso-insured loans are associated with increased likelihood of loan received and loan approval for male farmers. We speculate that banks may trust females more due to their higher creditworthiness and therefore, they do not care whether the insurance payouts go to the females or the banks. However, with males having a lower history of repayments (compared to males), banks may not trust them to repay if the payout goes to males (Buchan, Croson, and Solnick 2008; D'Espallier, Guérin, and Mersland 2011). The meso-insured loan guarantees repayment in case of a payout which may give the banks confidence to lend to males. Therefore, policymakers can think of offering differentiated products to increase credit access across the board for smallholders. Additionally, 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. Lastly, we do not find any statistically significant association between any of the insured loans for loan application for either male or female farmers. We believe this could be because our sample has an average loan application rate of 91% in the baseline period. 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 protect production would be to introduce drought resistance seeds along with the insurance component.

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Tables and Figures

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

Parameters	Definitions	Values
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_L	Penality for default	.5
κ	Cost of application	.1
Y_H	High yield with improved technology	$(EY - (1-p) * Y_L)/p$
Y_L	Low yield with improved technology	$[(\kappa + C - \omega) + 0.01\,, \frac{R}{q} - 0.01]$
Y_t	Output with traditional seed	5
C	Collateral value	.5
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

Table 2 - Heteregeneity in base parameter values and corresponding predicted application rates for females and males

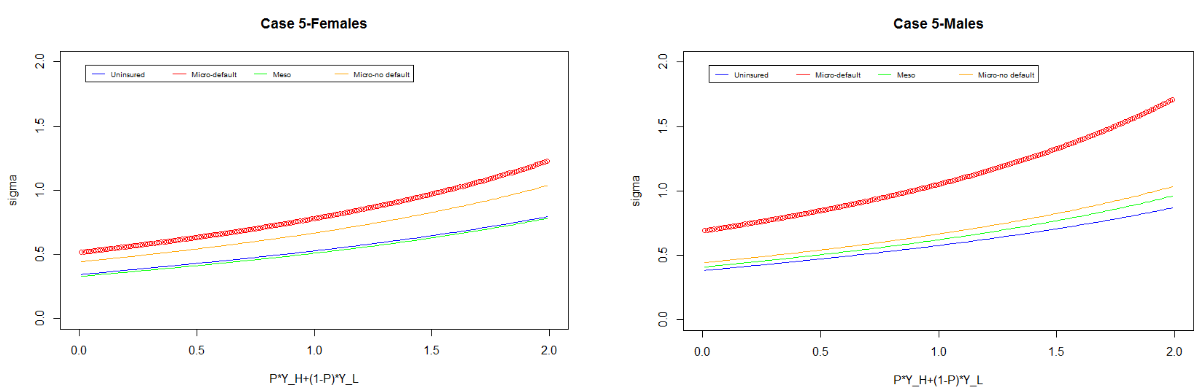
Panel A: Base parameters for males and females		
Parameters	Case 1– Females	Case 2– Males
τ	**.3**	**.7**
C	**.7**	**.5**
φ_L	**1**	**.6**
P_{ME}	.9	.9
P_{MI}	.8	**.7**
P_U	**.8**	**.6**

Panel B: Simulation results of proportion of population that apply for loans

Micro-Default	.9956	1.000
Micro-No Default	.9817	.9833
Meso	.9028	.9586
Uninsured	.8925	.9225

Application simulations assume $Y_L = 1$, and a population of idividuals with CRRA coefficients drawn from a normally distribution with mean $\mu = .3$ 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-Females are with both low trust and medium penalty, but high collateral value; and Case 2-Males are with high trust, but low collateral and penalty values.

Table 3 – Descriptive Statistics and Mean ttest comparison of selected baseline variables by Gender

	Males		Females		
Variables	Mean	SD	Mean	SD	P-value
Saving (1 = yes)	0.631841	0.482906	0.721485	0.448864	0.00
Outstanding Debt (1 = yes)	0.186567	0.390049	0.209549	0.407528	0.42
Default (1 = yes)	0.157	0.365	0.162	0.372	0.58
Land cultivated with maize (acres)	3.389884	4.636152	2.380449	1.726483	0.00
Number of Plots used	3.052239	1.129852	2.954907	0.945641	0.19
Number of cattle	4.708955	8.092198	3.259947	5.565023	0.00
Agricultural income (Ghana Cedis)	1525.124	977.3542	1293.236	925.6255	0.00
Remittance income (Ghana Cedis)	108.9652	219.445	91.17772	185.9562	0.22
Household size	9.099503	3.389885	7.66313	3.047591	0.00
Respondent age	44.87811	13.25701	44.72267	12.15906	0.86
Number of help during drought	1.970149	3.993024	2.037135	2.290986	0.77
Good season 5	2.330846	0.930231	2.411141	0.904	0.22
Risk aversion (5-point Likert scale)	2.125628	1.06905	2.134409	1.055444	0.91
Previous borrower (1 = yes)	0.701493	0.458174	0.766578	0.42357	0.04

Table 4 – Mean t-test comparisons of outcome variables

Variables	Non-insured loan	Micro-insured loan		Meso-insured loan	
Panel A - Females					
Baseline					
Loan received	0.723214	0.772727		0.721805	
Apply	0.946429	0.954545		0.954887	
Approve	0.764151	0.809524		0.755906	
Follow-up 1					
Loan received	0.482143	0.75	***	0.684211	***
apply	0.732143	0.863636	***	0.819549	
approve	0.658537	0.868421	***	0.834862	***
Follow-up 2					
Loan received	0.36036	0.363636		0.515152	**
apply	0.576577	0.477273		0.712121	**
approve	0.625	0.761905	*	0.723404	
Panel B - Males					
Baseline					
Loan received	0.693878	0.697674		0.571429	**
apply	0.897959	0.906977		0.833333	
approve	0.772727	0.769231		0.685714	
Follow-up 1					
Loan received	0.55102	0.651163	*	0.666667	*
apply	0.77551	0.837209		0.761905	
approve	0.710526	0.777778		0.875	***
Follow-up 2					
Loan received	0.272109	0.333333		0.301587	
apply	0.578231	0.48062		0.571429	
approve	0.470588	0.693548	***	0.527778	

Table 5 – Linear Probability Model for Loan-Received Variable

VARIABLES	Female DID	Male DID	Female FE	Male FE
micro-insured loan	-0.029	-0.027		
	(0.070)	(0.085)		
meso-insured loan	-0.041	-0.158*		
	(0.072)	(0.087)		
follow-up1	-0.241***	-0.143	-0.241***	-0.143
	(0.089)	(0.088)	(0.089)	(0.087)
follow-up2	-0.368***	-0.422***	-0.368***	-0.422***
	(0.078)	(0.081)	(0.078)	(0.080)
micro-insured loan#follow-up1	0.218*	0.096	0.218*	0.096
	(0.118)	(0.124)	(0.117)	(0.123)
micro-insured loan#follow-up2	-0.041	0.057	-0.041	0.057
	(0.127)	(0.119)	(0.126)	(0.118)
meso-insured loan#follow-up1	0.203*	0.238*	0.203*	0.238**
	(0.117)	(0.120)	(0.116)	(0.120)
meso-insured loan#follow-up2	0.162	0.152	0.161	0.152
	(0.124)	(0.122)	(0.123)	(0.121)
borrower	0.315***	0.288***	-0.063	0.000
	(0.052)	(0.044)	(0.041)	(.)
Constant	0.832***	0.816***	0.789***	0.657***
	(0.074)	(0.082)	(0.042)	(0.029)
Observations	1,129	1,206	1,129	1,206
R-squared	0.442	0.385	0.175	0.204
Bank dummies	YES	YES	--	--
Number of grpID	--	--	125	133

Table 6 - Linear Probability Model for Loan Application Variable

VARIABLES	Female DID	Male DID	Female FE	Male FE
micro-insured loan	-0.019	-0.010		
	(0.047)	(0.065)		
meso-insured loan	-0.023	-0.069		
	(0.050)	(0.072)		
follow-up1	-0.214***	-0.122*	-0.214***	-0.122*
	(0.078)	(0.069)	(0.078)	(0.069)
follow-up2	-0.370***	-0.320***	-0.368***	-0.320***
	(0.088)	(0.080)	(0.088)	(0.080)
micro-insured loan#follow-up1	0.123	0.053	0.123	0.053
	(0.095)	(0.093)	(0.095)	(0.092)
micro-insured loan#follow-up2	-0.107	-0.107	-0.110	-0.107
	(0.117)	(0.110)	(0.116)	(0.110)
meso-insured loan#follow-up1	0.079	0.051	0.079	0.051
	(0.099)	(0.105)	(0.099)	(0.105)
meso-insured loan#follow-up2	0.129	0.058	0.126	0.058
	(0.114)	(0.124)	(0.113)	(0.123)
borrower	0.036	0.008		
	(0.046)	(0.059)		
Constant	1.137***	1.133***	0.952***	0.881***
	(0.068)	(0.076)	(0.022)	(0.025)
Observations	1,129	1,206	1,129	1,206
R-squared	0.337	0.236	0.234	0.197
Bank dummy	YES	YES		
Number of grpID			125	133

Table 7 - Linear Probability Model for Loan Approval Variable

VARIABLES	Female DID	Male DID	Female FE	Male FE
micro-insured loan	-0.013	-0.047		
	(0.065)	(0.076)		
meso-insured loan	-0.060	-0.165**		
	(0.067)	(0.082)		
follow-up1	-0.136	-0.083	-0.149	-0.029
	(0.100)	(0.093)	(0.102)	(0.094)
follow-up2	-0.161**	-0.330***	-0.192**	-0.258***
	(0.079)	(0.095)	(0.079)	(0.098)
micro-insured loan#follow-up1	0.174	0.089	0.189	0.045
	(0.125)	(0.123)	(0.125)	(0.126)
micro-insured loan#follow-up2	0.123	0.206	0.223	0.233
	(0.132)	(0.136)	(0.137)	(0.142)
meso-insured loan#follow-up1	0.239**	0.295**	0.256**	0.252**
	(0.119)	(0.120)	(0.120)	(0.122)
meso-insured loan#follow-up2	0.171	0.222	0.208*	0.167
	(0.115)	(0.145)	(0.119)	(0.150)
borrower	0.353***	0.368***	-0.075	0.000
	(0.058)	(0.042)	(0.048)	(.)
Constant	0.678***	0.687***	0.831***	0.723***
	(0.082)	(0.078)	(0.045)	(0.028)
Observations	885	891	885	891
R-squared	0.474	0.410	0.040	0.099
Bank dummies	YES	YES	--	--
Number of grpID	--	--	122	127

Appendix Tables

Table 8 – Rounds combined

	Have-loan		Apply		Approve	
VARIABLES	Females	Males	Females	Males	Females	Males
follow-ups combined	-0.303***	-0.282***	-0.291***	-0.221***	-0.114	-0.157**
	(0.072)	(0.077)	(0.069)	(0.066)	(0.070)	(0.079)
micro-insured loan	0.030	0.013	0.001	0.015	0.043	-0.011
	(0.065)	(0.076)	(0.049)	(0.063)	(0.056)	(0.066)
meso-insured loan	-0.027	-0.108	-0.002	-0.062	-0.022	-0.083
	(0.071)	(0.079)	(0.050)	(0.071)	(0.060)	(0.065)
micro-insured loan#follow-up s combined	0.087	0.077	0.007	-0.027	0.160	0.140
	(0.106)	(0.106)	(0.085)	(0.085)	(0.098)	(0.103)
meso-insured loan#follow-ups combined	0.182*	0.195*	0.103	0.054	0.162*	0.216*
	(0.104)	(0.108)	(0.086)	(0.101)	(0.096)	(0.112)
borrower	0.481***	0.374***	0.094**	0.057	0.528***	0.464***
	(0.058)	(0.048)	(0.044)	(0.055)	(0.058)	(0.054)
Constant	0.425***	0.424***	1.013***	0.877***	0.300***	0.427***
	(0.073)	(0.068)	(0.054)	(0.063)	(0.069)	(0.069)
Observations	1,129	1,206	1,129	1,206	885	891
R-squared	0.209	0.160	0.146	0.062	0.329	0.232

Table 9 – Group level analysis

VARIABLES	Female	Male	Female	Male	Female	Male
	Have Loan		Apply		Approve	
			Panel A - DID			
follow-up1	-0.267***	-0.205***	-0.273***	-0.216***	-0.215**	-0.132
	(0.076)	(0.077)	(0.089)	(0.080)	(0.091)	(0.085)
follow-up2	-0.395***	-0.420***	-0.464***	-0.411***	-0.261***	-0.273***
	(0.066)	(0.069)	(0.085)	(0.080)	(0.079)	(0.091)
micro-insured loan	0.044	-0.006	0.028	0.011	0.023	-0.021
	(0.066)	(0.073)	(0.072)	(0.072)	(0.052)	(0.061)
meso-insured loan	-0.031	-0.132*	-0.023	-0.072	-0.029	-0.113*
	(0.067)	(0.072)	(0.076)	(0.081)	(0.052)	(0.061)
micro-insured loan#follow-up1	0.188*	0.126	0.147	0.085	0.218*	0.140
	(0.111)	(0.116)	(0.118)	(0.114)	(0.121)	(0.125)
micro-insured loan#follow-up2	-0.009	0.011	-0.085	-0.141	0.251*	0.150
	(0.097)	(0.100)	(0.113)	(0.111)	(0.136)	(0.133)
meso-insured loan#follow-up1	0.232**	0.248**	0.118	0.066	0.329***	0.341***
	(0.107)	(0.113)	(0.120)	(0.123)	(0.108)	(0.113)
meso-insured loan#follow-up2	0.151	0.148	0.164	0.077	0.171	0.118
	(0.098)	(0.102)	(0.119)	(0.123)	(0.116)	(0.132)
borrower	0.448***	0.410***	0.121**	0.072	0.636***	0.581***
	(0.041)	(0.040)	(0.053)	(0.050)	(0.050)	(0.050)
Constant	0.274***	0.356***	0.835***	0.887***	0.185***	0.281***
	(0.054)	(0.056)	(0.074)	(0.068)	(0.048)	(0.054)
Region dummies	YES	YES	YES	YES	YES	YES
Observations	555	540	476	477	372	357
R-squared	0.267	0.240	0.203	0.174	0.393	0.338
			Panel B – Group level analysis, Fixed effects Model			
VARIABLES	Female	Male	Female	Male	Female	Male
follow-up1	-0.243***	-0.143	-0.216***	-0.122*	-0.158	-0.031
	(0.090)	(0.088)	(0.079)	(0.069)	(0.104)	(0.094)
follow-up2	-0.369***	-0.422***	-0.369***	-0.320***	-0.211**	-0.256**
	(0.078)	(0.081)	(0.088)	(0.080)	(0.084)	(0.098)
micro-insured loan#follow-up1	0.221*	0.096	0.125	0.053	0.198	0.047
	(0.118)	(0.124)	(0.096)	(0.093)	(0.127)	(0.127)
micro-insured loan#follow-up2	-0.040	0.057	-0.108	-0.107	0.242*	0.219
	(0.127)	(0.119)	(0.117)	(0.110)	(0.140)	(0.145)
meso-insured loan#follow-up1	0.198*	0.240**	0.080	0.049	0.257**	0.261**
	(0.115)	(0.121)	(0.100)	(0.107)	(0.120)	(0.124)
meso-insured loan#follow-up2	0.157	0.170	0.127	0.076	0.204	0.169

	(0.122)	(0.120)	(0.114)	(0.121)	(0.124)	(0.151)
Constant	0.744***	0.654***	0.952***	0.880***	0.778***	0.720***
	(0.029)	(0.029)	(0.022)	(0.025)	(0.025)	(0.029)
Observations	375	399	375	399	295	296
R-squared	0.182	0.204	0.237	0.196	0.046	0.104
Number of grpID	125	133	125	133	122	127

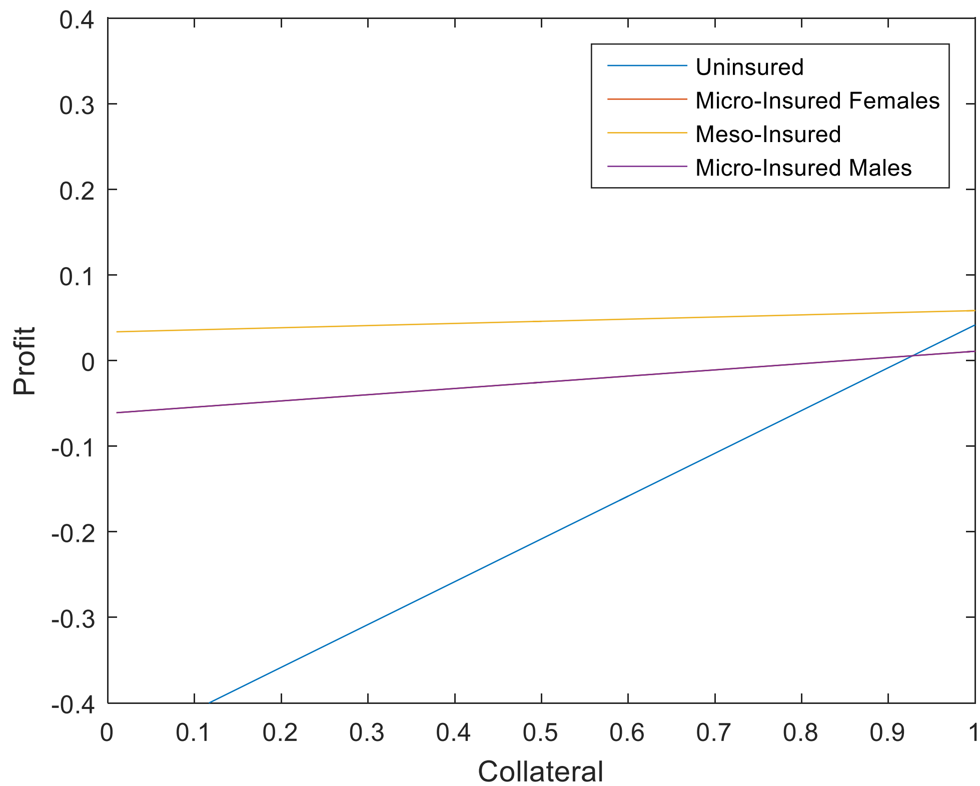
Table 10 – Propensity score matching – loan approval outcome variable

VARIABLES	Mico-insured loans		Meso-insured loans	
	Female	Male	Female	Male
follow-up1	-0.150	-0.046	-0.158	-0.046
	(0.105)	(0.094)	(0.111)	(0.095)
follow-up2	-0.196**	-0.253**	-0.208**	-0.256**
	(0.082)	(0.102)	(0.087)	(0.103)
micro-insured loan#follow-up1	0.190	0.073		
	(0.125)	(0.128)		
micro-insured loan#follow-up2	0.253*	0.231		
	(0.136)	(0.148)		
pscore	-0.021	0.030	0.040	0.011
	(0.022)	(0.034)	(0.040)	(0.035)
meso-insured loan#follow-up1			0.267**	0.279**
			(0.129)	(0.126)
meso-insured loan#follow-up2			0.249**	0.174
			(0.123)	(0.159)
Constant	0.819***	0.742***	0.745***	0.723***
	(0.031)	(0.036)	(0.033)	(0.040)
Observations	533	573	539	539
R-squared	0.044	0.057	0.060	0.131
Number of grpID	77	81	73	75

Table A1: Definition of parameters and their value for Supply 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 & males strategically defaulting	.05 & .1
π	Insurance premium for the loans	$\left(\frac{1-q}{q}\right)K$

Figure 2: Profit functions for insured and unsured loans



The profit functions are based on a higher default rate for females $(\lambda = 0.05)$ than males $(\lambda = 0.1)$.