

Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi*

Xavier Giné

Development Economics Research Group, World Bank
and Bureau for Research and Economic Analysis of Development (BREAD)

Dean Yang

Ford School of Public Policy and Department of Economics, University of Michigan;
Bureau for Research and Economic Analysis of Development (BREAD);
and National Bureau of Economic Research (NBER)

September 2007

Abstract

Adoption of new agricultural technologies may be discouraged by their inherent riskiness. We implemented a randomized field experiment to ask whether provision of insurance against a major source of production risk induces farmers to take out loans to invest in a new crop variety. The study sample was composed of roughly 800 maize and groundnut farmers in Malawi, where by far the dominant source of production risk is the level of rainfall. We randomly selected half of the farmers to be offered credit to purchase high-yielding hybrid maize and groundnut seeds for planting in the November 2006 crop season. The other half of farmers were offered a similar credit package, but were also required to purchase (at actuarially fair rates) a weather insurance policy that partially or fully forgave the loan in the event of poor rainfall. Surprisingly, take up was lower by 13 percentage points among farmers offered insurance with the loan. Take-up was 33.0% for farmers who were offered the uninsured loan. There is suggestive evidence that reduced take-up of the insured loan was due to the high cognitive cost of evaluating the insurance: insured loan take-up was positively correlated with farmer education levels. By contrast, take-up of the uninsured loan was uncorrelated with farmer education.

Keywords: risk-sharing, insurance, credit, microfinance, technology adoption

* Gine: xgine@worldbank.org. Yang: deanyang@umich.edu. We gratefully acknowledge financial support from CRMG (World Bank) and in particular the support of Erin Bryla, Shadreck Mapfumo and Frank Masanka. We also thank Ephraim Chirwa and the Wadonda team for their efforts in collecting the data. We received valuable feedback and suggestions from Chris Ahlin, Steve Boucher, Adriana Lleras-Muney, Eldar Shafir, and participants in several seminars. Paola de Baldomero Zazo, Jessica Goldberg and Cheryl Raleigh provided superb research assistance.

1. Introduction

The adoption of new technology plays a fundamental role in the development process. In the 1950s and 1960s, the so-called Green Revolution transformed agricultural production in developing countries by introducing high-yield crop varieties and other modern cultivation practices. While the modernization of production brought about significant increases in agricultural productivity and growth, the impact of the Green Revolution has been uneven. There is enormous variation, within regions and between regions, in the extent to which households have benefited from the availability of these new technologies.¹

Among the often cited reasons why technology has failed to diffuse, aversion to risk, credit constraints and limited access to information are leading candidates (Feder, Just and Zilberman, 1985).² Undoubtedly, production risk is a major source of income fluctuations for rural households involved in agricultural activities, especially in developing countries. Because high yield varieties are more profitable but also riskier, households unwilling to bear consumption fluctuations may decide not to adopt. In addition, in policy circles the lack of access to credit has traditionally been considered a major obstacle to technology adoption and development.³

¹ See Griliches (1957) on adoption of hybrid corn in the United States, Evenson (1974) on diffusion of agricultural technologies internationally, and Goldman (1993) on technology adoption across regions in Kenya.

² See Evenson and Westphal (1995), Rogers (1995) and Munshi (forthcoming) for a more recent review. See also the introduction in Conley and Udry (2005) for references, as well as Besley and Case (1994). Recent work on technology adoption and social learning includes Foster and Rosenzweig (1995), Munshi (2004), Conley and Udry (2005), and Duflo, Kremer, and Robinson (2006).

³ The following quote from 1973 by Robert McNamara when he was the World Bank president exemplifies this view: “The miracle of the Green Revolution may have arrived, but for the most part, the poor farmer has not been able to participate in it. He simply cannot afford to pay for the irrigation, the pesticide, the fertilizer... For the small holder operating with virtually no capital, access to capital is crucial”.

With complete and frictionless financial markets, fluctuations would not be a source of concern as households would be able to protect consumption, and credit would flow to activities with the highest marginal return. But in developing countries, insurance and credit markets are typically incomplete or altogether absent. In this environment, the separation of consumption and production decisions may not obtain (Benjamin, 1992), and thus, the relative importance of credit constraints and risk aversion may be confounded (Chaudhuri and Osborne, 2002).

This last point is illustrated by the well-known positive correlation between wealth and adoption of new technology.⁴ Some have argued that this correlation provides evidence for credit constraints, because wealthier farmers have better access to credit and thus face lower financial constraints to adopt. However, even if we ignore that unobserved heterogeneity (correlated with wealth) may be ultimately responsible for the observed correlation, under plausible assumptions wealthier households will also be more tolerant of risk. Therefore, it is not clear whether the correlation is driven by credit constraints and thus imperfections in the credit market, or by risk aversion and therefore lack of insurance instruments to hedge risk. Disentangling the two explanations is crucial because they call for very different government interventions.

This paper describes the findings of a randomized field experiment we implemented testing whether bundling insurance with credit increased farmers' willingness to adopt a new technology. The specific context of the study was the adoption of high-yield hybrid varieties of maize and groundnut among small landholders in Malawi. Nearly all Malawian households (97% in 2004-2005) are engaged in maize production, but only 58% use hybrid maize varieties (World Bank 2006). Smale and

⁴ See Feder, Just, and Zilberman (1985), Just and Zilberman (1983), Besley and Case (1993).

Jayne (2003) note that hybrid maize adoption in Malawi has lagged behind adoption in Kenya, Zambia, and Zimbabwe.

Existing studies document that hybrid seed use in Malawi is correlated with wealth and other indicators of household socioeconomic status. Data from the country's nationally-representative Integrated Household Survey conducted in 2004-2005 documents higher adoption of hybrid maize among households in the highest quintile of land ownership (66%) than in the lowest quintile (53%) (World Bank 2006). Among maize farmers in southern Malawi, Chirwa (2005) finds that close to 60% do not use hybrid maize varieties, and that adoption rises in income, education, and plot size. Simtowe and Zeller (2006) find higher maize adoption among households with access to credit. Due to the potential correlation between access to credit and ability (or willingness) to cope with risk, it is unclear in these studies whether credit constraints or absence of insurance markets (or both) are the key constraints hindering hybrid seed adoption in Malawi.

To test the importance of risk in hindering hybrid seed adoption, we randomized whether farmers' loans to purchase hybrid seeds were insured against rainfall risk, by far the dominant source of production risk in Malawi. The study sample was composed of roughly 800 maize and groundnut farmers. We randomly selected half of the farmers to be offered credit to purchase high-yielding hybrid maize and groundnut seeds for planting in the November 2006 crop season. The other half of farmers were offered a similar credit package, but were also required to purchase (at actuarially fair rates) a weather insurance policy that partially or fully forgave the loan in the event of poor rainfall.

If borrowers are risk averse while the lender is not, a standard debt contract (credit only) will in general not be optimal because it requires that the borrower bear all the risk when he or she is the least prepared to bear it. But in the presence of informational asymmetries (requiring verification costs) or under bounded rationality, the simplicity of the debt contract may indeed be close to being optimal (see Dowd, 1992 for a review).

In any event, the requirement in a debt contract that repayment be non-contingent may be responsible for a lower demand for credit as prospective borrowers fear the loss in utility associated to having to repay even when production fails. In other words, risk averse borrowers may prefer planting a traditional variety that does not require credit, to adopting the hybrid variety that is riskier.⁵ In this situation, the provision of insurance should in principle *raise* adoption among risk-averse farmers.

Our experimental results are at odds with this prediction. Take-up was 33.0% among farmers who were offered the basic loan without insurance. Surprisingly, take up was lower, at only 17.6%, among farmers whose loans were insured against poor rainfall.

A variety of behavioral and boundedly rational explanations may be behind this surprising result. Insured loan take-up was positively correlated with farmer education levels; by contrast, uninsured loan take-up was uncorrelated with farmer education. This suggests that reduced take-up of the insured loan may have been due to the high cognitive cost of evaluating a complex insurance product. Most farmers were being exposed to an insurance product for the first time, and may not have understood the concept or the complicated payout schedule (which depended on the level as well as timing of rainfall).

⁵ Dercon and Christiaensen (2007) provide evidence that consumption risk discourages fertilizer use by Ethiopian farmers. See also Binswanger and Sillers (1983) and Boucher et al. (2006).

This explanation is consistent with evidence on the dampening effect of complexity on take-up of social programs in developed nations. See, for example, the discussion in Bertrand, Mullainathan, and Shafir (forthcoming) in the context of the U.S. food stamp program.⁶

Other explanations for lower take-up of the insured loan may also apply. A rational explanation would be that farmers may simply have placed a low (in the extreme, zero) value on the insurance they were offered, perhaps because they mistrusted the insuring organization or doubted that rainfall measured at the local weather station would be highly correlated with their farm output (i.e, basis risk). Low valuation of insurance, in combination with very high price elasticity, could have caused low take-up of the credit plus insurance product. We believe this explanation cannot be sufficient because the price elasticity of credit demand would have to be extremely large to explain the full decline in take-up, although it could explain some modest portion of the decline. In addition, an explanation from the psychology literature is that offering the insured loan may have primed farmers to weight risk considerations more highly in their adoption decision. In many settings psychologists have found that “priming” by highly local and temporary influences can have large effects on decision making. For example, Bornstein (1989) and Zajonc (1968) find that mere exposure can increase affinity for certain things.

The remainder of this paper is organized as follows. In Section 2 we describe the experimental design and the survey data. We describe the main empirical results on the impact of the insurance on take-up in Section 3, and then in Section 4 explore a variety of determinants of take-up separately in the treatment and control groups. Section 5 assesses the evidence for a variety of explanations for lower take-up in the insured group.

⁶ See also Duflo, Gale, Liebman, Orszag, and Saez (2005) as well as Liebman and Zeckhauser (2004).

Section 6 concludes. Appendix A develops a simple model of technology adoption under uncertainty that is later extended to account for complexity. Finally, Appendix B provides further details on the variables used in the empirical analysis.

2. Experimental Design and Survey Data

The experiment was carried out as part of the Malawi Technology Adoption and Risk Initiative (MTARI), a cooperative effort among several partners: the National Smallholder Farmers Association of Malawi (NASFAM), Opportunity International Bank of Malawi (OIBM), the Malawi Rural Finance Corporation (MRFC), the Insurance Association of Malawi (IAM), and the Commodity Risk Management Group (CRMG) of the World Bank. NASFAM is an NGO that provides technical assistance and marketing services to nearly 100,000 farmers in Malawi. It is by far the largest farmer association in the country. The farmers in the study were current NASFAM members. NASFAM field officers disseminated the information on the insured and uninsured loans to farmers, and handled the logistics of supplying farmers with the hybrid seeds purchased on credit. OIBM and MRFC are microfinance lenders and provided the credit for purchase of the hybrid seeds. OIBM is a member of the global Opportunity International network of microfinance institutions, while MRFC is a government-owned corporation. IAM designed and underwrote the actual insurance policies with technical assistance from the World Bank.

The microfinance institutions offered the loans for the hybrid seeds as group liability contracts for clubs of 10-20 farmers. Take-up of the loan was an individual

decision, however, and only the subset of farmers who took up the loan were jointly liable for each others' loans. NASFAM contacted clubs in June and July 2006 and offered them the opportunity to be included in the study. Our study sample consists of 159 clubs from four different regions of central Malawi: Lilongwe North, Mchinji, Kasungu, and Nkhotakota. Figure 1 shows the study locations. In these clubs there were 787 farmers who agreed to be part of the study and were available to be surveyed in the following September.

To minimize concerns about fairness if farmers discovered that other farmers in the study were being treated differently, the treatments were randomized at the level of 32 localities. Each locality has roughly 4 clubs from neighboring villages. Localities were randomized into two equal sized groups: 16 "uninsured" (control) localities and 16 insured (treatment) localities. Figure 2 plots the location of control (in red) and treatment (in black) farmers. The 394 farmers from "uninsured" localities were simply offered a loan (standard debt contract) for the hybrid seeds, while the 393 farmers from "insured" localities were not only offered the loan for the hybrid seeds (identical to the "uninsured" one) but they also received a rainfall insurance policy with an approximately actuarially-fair premium. In this insured loan group, farmers were required to take the insurance if they wanted the loan package.

Farmers were given the option to purchase an improved groundnut only or improved groundnut and a hybrid maize seed and fertilizer package.⁷ In order to obtain either package, a deposit of 12.5 percent of the package amount was required in advance. The uninsured groundnut loan package provided enough seed (32 kg.) of an improved

⁷ The option of a maize seed and fertilizer only was not given because maize is typically for consumption, and thus NASFAM and the lenders wanted to ensure repayment of the loan using the proceeds from the sale of groundnut, a cash crop.

variety (ICGV-SM 90704) for planting on one acre of land, with a total of MK 4,692.00 to be repaid at harvest time 10 months later (roughly US\$33.51).⁸ Of this total repayment, MK 3,680 was the cost of seed and MK 1,012.00 was interest. Farmers offered the insured groundnut package were in addition charged for the insurance premium, which ranged from MK 297.98 in Nkhotahota to MK 529.77 in Lilongwe (about 6 to 10 percent of the uninsured principal) so that the total repayment due at harvest time was between MK 5,130.07 and MK 5,367.45 (roughly US\$36.23-US\$38.34). The improved groundnut variety offered has several benefits over traditional varieties. First, it is higher yielding (more than double in field trials), is less susceptible to drought, has a shorter maturation period, exhibits greater disease resistance and has higher oil content.⁹

Corresponding costs for the hybrid maize package (which provided inputs sufficient for ½ acre of land) were as follows: MK 3,900 for seeds and fertilizer for a total uninsured package of MK 4,972.50 (US\$35.52) and an insurance premium that ranged from MK647.16 to MK 1,082.29, depending on the reference weather station. Like the improved groundnut seed, hybrid maize is bred to be disease resistant and high-yielding. In pre-release trials in mid-altitude areas of Malawi, DK 8051 had higher yield than all comparison varieties. It outperformed the trial mean by 12.7 percent, and outperformed MH18, another hybrid variety used by farmers in our sample, by 32.7 percent. The DK8051 is also resistant to common diseases including GLS, leaf blight, and other conditions (see Wessels, 2001 for details).

⁸ In October 2006, roughly 140 Malawi kwacha (MK) were convertible to US\$1.

⁹ Although the improved groundnut seed is more resistant to drought, farmers typically have to borrow to pay for the seeds, so it may appear overall as a riskier choice if the farmer has to pledge assets as collateral or will be denied future credit in case of default.

The insurance policy bundled with the loan pays out a proportion (or the totality) of the principal and interest depending on the level of rainfall. In other words, the insured loan is in essence a *contingent* loan whose repayment amount depends on the realization of rainfall at the nearest weather station. The coverage for both maize and groundnut policies is for the rainy season, which is the prime cropping season, running from September to March. The contract divides the cropping season into three phases (sowing, podding/flowering and harvest) and pays out if rainfall levels fall below particular threshold or “trigger” values during each phase. As Figure 3 shows for a given phase, an upper and lower threshold is specified for each of the three phases. If accumulated rainfall exceeds the upper threshold, the policy pays zero for that phase. Otherwise, the policy pays a fixed amount for each millimeter of rainfall below the threshold, until the lower threshold is reached. If rainfall falls below the lower threshold, the policy pays a fixed, higher payout. The total payout for the cropping season is then simply the sum of payouts across the three phases. The maximum payout corresponds to the total loan amount for seeds and the premium and the interest payment.

The timing of the phases, thresholds and other parameters of the model were determined using crop models specific to improved groundnut and hybrid maize as well as interactions with individual farmers. During the baseline survey, when farmers were asked what affects groundnut production the most, close to 70 percent said rainfall, and less than 20 percent said pests, the next reason in importance. The upper threshold corresponds to the crop’s water requirement or the average accumulated rainfall at the rainfall gauge (whichever is lowest), while the second trigger is intended to capture the water requirement necessary to avoid complete harvest failure. Translated into financial

market terminology, the relationship between rainfall and payoffs resembles a “put spread” option for each phase. The insurance policy’s premium payment was calculated based on projected payouts using historical rainfall data, plus a 17.5% government-mandated surtax.

All farmers in the study were administered a household socioeconomic survey in September 2006. The survey covered income, education, assets, income-generating activities (including detailed information on crop production and crop choice), measures of risk aversion, and knowledge about financial products such as credit and insurance.

After the completion of the survey, an orientation meeting was held in each of the 32 localities in October 2007 where NASFAM field officers explained the loan product being offered (insured or uninsured) to the study farmers. Farmers then had two weeks to decide whether to take up the loan, which required a deposit of 12.5% of the loan amount at the local NASFAM field office. Seeds and fertilizer were then delivered to pre-specified collection points near the club meeting place, and planting occurred with the beginning of the rains in November.

Summary statistics from the baseline survey are presented in Table 1, and variable definitions are provided in Appendix B.

3. Empirical results

In what follows, the “treatment group” refers to farmers who were offered the insured loan, and the “control group” refers to farmers offered the uninsured loan. Randomization of treatment should ensure that treatment and control groups have similar

baseline characteristics on average. To check this, Table 2 presents means of several key farmer and household characteristics for the treatment and control groups, as well as the p-value of the F-test that the difference in means is statistically significantly different from zero.

For nearly all the variables presented (gender of the respondent, female headship of the respondent's household, household income, respondent's age, land ownership, risk tolerance, having experienced a drop in income due to drought, trust in the insurance company and an index of housing quality constructed from indicators for various household amenities), the difference in means is not statistically different from zero. The sole exception is that years of education among treatment group respondents is 0.82 years lower than in the control group, and this difference is statistically significant at the 10% level. As farmer years of education is a key variable (and will later be shown to be positively correlated with take-up), this is unfortunate. However, we will provide evidence later that lower education in the treatment group can only go a very small way towards explaining their lower take-up rates. We also take comfort in the fact that we cannot reject the hypothesis that all the variables are jointly insignificant, since the F-test yields a p-value of 0.38.

Because the various treatments are assigned randomly at the locality level, the impact of the treatment on take-up of the hybrid seed loan can be estimated via the following regression equation:

$$(1) \quad Y_{ij} = \alpha + \beta I_j + \delta X_{ij} + \phi_j + \varepsilon_{ij}.$$

where Y_{ij} = adoption decision for individual i in locality j (1 if adopting and 0 otherwise), I_j is insurance status (1 if the loan is insured and 0 otherwise), X_{ij} are individual-level pre-baseline control variables, and ϕ_j are fixed effects for four study regions. ε_{ij} is a mean-zero error term. Treatment assignment at the locality level creates spatial correlation among farmers within the same locality, so standard errors are clustered at the locality level (Moulton 1986).

The coefficient β on the insurance dummy variable is the impact of being offered insurance on adoption, and answers the question “How much does insurance raise demand for the hybrid seed loan?” Due to the randomization of treatment, controls for baseline variables should not strictly be necessary, and in practice have little effect on the estimated treatment effect β , but they do help absorb residual variation and reduce standard errors. In addition, it is useful to include a control for farmer education because, as discussed above, the locality-level randomization failed to eliminate statistically significant (at the 10% level) differences between the education levels of treatment and control respondents.

Table 3 presents estimates of regression equation (1) in specifications with various combinations of baseline control variables. Column 1 presents the simplest possible specification, where the only right hand side variable is the indicator for treatment. The treatment effect (-0.154) is negative and large in magnitude, although the coefficient is not statistically significantly different from zero at conventional levels (the t-statistic is 1.41).

Additional control variables for baseline characteristics in subsequent columns add explanatory power to the regression (as reflected in rising R-squared) and so help

reduce the standard error on the treatment coefficient while having minimal effects on the coefficient point estimate. Column 2 adds fixed effects for the four study regions, which reduces the magnitude of the point estimate slightly (to -0.141) but also reduces the standard error so that the estimate is now statistically significant at the 10% level.

In column 3, a variety of other control variables are additionally included in the regression (gender of the respondent, female headship of the respondent's household, household income, respondent's education, respondent's age, acres of land ownership, an index of housing quality and net income). The coefficient declines slightly to -0.132 as a result, and becomes only marginally statistically significant. Column 4 allows for more flexible functional forms for the continuous baseline control variables (respondent's education, household income, respondent's age, land ownership) by including dummy variables for each quintile of these variables. The coefficient estimate is now -0.128 and it has become more precise since it is again statistically significant at the 10% level.

Finally, because treatment farmers are less educated on average than control farmers, it is important to understand whether the control for respondent's years of education makes a substantial difference in the estimated coefficient. In column 5, the dummy variables for education are dropped from the regression. As it turns out, dropping these controls has very little effect: the coefficient on treatment, at -0.134, is very similar to the coefficient in the previous column where the education dummy variables are included.

The estimates indicate that bundling insurance with the hybrid seed loan led to roughly 13 percentage points lower take-up vis-à-vis the uninsured loan.

4. Determinants of take-up of insured and uninsured loans

Why were farmers less likely to take up the loan for the hybrid seeds when it was bundled with insurance? To fix ideas, Appendix A presents a simple model of a household with mean-variance expected utility. The benchmark model predicts that as long as the correlation between rainfall and income is positive and large enough, risk-averse agents should be unambiguously better off when offered insurance at an actuarially fair price with the loan. Thus, this theoretical prediction is at odds with the lower take-up for the insured loan found in Table 3.

Regressions in Table 4 provide evidence on the determinants of take-up in the two treatment conditions separately. The first four columns regress take-up on farmer characteristics for the treatment (insured loan) group, and the remaining four columns do the same for farmers in the control (uninsured loan) group.

Positive coefficients on education in the regressions for the treatment group indicate that better-educated farmers showed more interest in the insured loan product. The coefficient on years of education is 0.14 in the first three columns. The first column does not include region fixed effects, column two does include them, and column three includes risk tolerance as well as region fixed effects. In all three columns, the coefficient on years of education is statistically significantly different from zero at the 5% level.

Column 4 adds controls for a variety of other baseline characteristics (gender of the respondent, female headship of the respondent's household, household income, respondent's age, land ownership, and an index of house quality) to test whether the association with education may reflect the influence of omitted variables. The coefficient

on years of education falls to 0.009, but remains statistically significant from zero at the 10% level. The coefficient on education in column 4 suggests that one additional year of education lowers the likelihood of take-up by roughly one percentage point. In addition, farmers that reported higher trust in the insurance company underwriting the insurance policy were also more likely to take-up the insured loan. The coefficient on trust in insurance company is positive and marginally significant (p-val is 0.11), and suggests that an increase of 1 point in a 0-10 scale raises the likelihood of take-up by 1 percentage point.

These results are suggestive that the insurance component was too complex for relatively uneducated farmers to understand, thus hindering take-up of the insured loan. Most farmers were being exposed to an insurance product for the first time, and may not have understood the concept or the complicated payout schedule (which depended on the level as well as timing of rainfall). In addition, lack of trust in the insurance provider may have hindered uptake.

Another piece of evidence that indirectly supports the complexity story is from a question in the baseline where farmers had to guess on a sheet of paper with a ruler drawn to scale the length of 60 millimeters. Farmers typically assess rainfall levels not in millimeters but in depth of ground moisture. Yet, the insurance policy triggers were all in millimeters. The results clearly suggest that farmers have little understanding of the concept of a millimeter. The ruler had letters A to F at intervals of 30 mm. So A was at 30 mm, B at 60 mm and so forth, until F at 180 mm. Farmers were asked to report the letter that was located 60 mm from one end of the ruler. Although only 2.3 percent of the farmers said they didn't know, only 11.6 percent reported B as the right answer. A full 28

percent gave C as the right answer (located in the middle of the ruler), and another 23 percent answered F (located at the end of the ruler).

This complexity interpretation is consistent with evidence from other contexts (primarily in the developed world) that the complexity of social programs inhibits use by target populations. Bertrand, Mullainathan, and Shafir (forthcoming) argue that the complexity of the forms required for food stamp participants in the U.S. may be an important factor inhibiting program participation. In a field experiment, Duflo, Gale, Liebman, Orszag, and Saez (2005) find much higher response to matching incentives for IRA contributions than is found in the U.S. tax code's Savers Credit program. They attribute the higher response in their experiment to the fact that the Savers Credit program is quite complicated to decipher. Liebman and Zeckhauser (2004) show that individuals in the U.S. have a poor understanding of their income tax schedule. If complexity issues arise even in the relatively well-educated U.S. population, they are likely to loom even larger for low-education Malawian farmers.

In the model of Appendix A, complexity is modeled as a distortion in the perceived correlation between rainfall and income, such that the higher the complexity, the lower the correlation.

Determinants of the take up of the uninsured loan product are examined in the remaining four columns of the table. In column 5, the coefficient on education is positive and statistically significantly different from zero at conventional levels, but the coefficient falls very close to zero and becomes statistically insignificant when controls for region and other baseline characteristics are added. In contrast to the results for the insured loan, take-up of the uninsured loan does not appear to be correlated with farmer

education levels when controlling for other farmer and locality characteristics. A likely explanation is that the uninsured loan was simple enough to understand for even the least-educated farmers: no complicated insurance payout structure had to be explained.

It is interesting to note that take up of uninsured loan is positively associated with farmers' self-reported risk tolerance. In column 7, the coefficient on risk tolerance (0.015) is positive and highly statistically significantly different from zero. A one-point increase in self-reported risk tolerance (on a scale of 0-10) leads to a 1.5 percentage point increase in the likelihood of taking up the uninsured loan. In column 8, the coefficient remains at 0.015 and is still highly significant. Also noteworthy is the fact that households that suffered a decline in income due to drought in the past 5 years are less likely to take any loan, although the coefficient is more precisely estimated for the uninsured loan. These results suggest that risk considerations do affect farmer interest in taking out loans for the new hybrid seeds. That farmers nonetheless did not exhibit higher take-up when offered the insured loan suggests that other factors coinciding with being offered the insured loan dramatically offset any risk-reduction effect of the insurance.

5. Discussion and further evidence

It is useful at this point to address other potential explanations for the difference in take-up across the two groups.

Differences in mean education levels across treatment and control groups

Given that education is positively correlated with take-up of the insured loan, a valid concern is that some part of the observed difference in take-up between the treatment and control groups may be due to the fact that the treatment group had 0.823 fewer years of education on average than the control group (see Table 2). The coefficient on education in column 4 of Table 4 indicates that this difference in average years of education should account for roughly 0.00823 (0.823 percentage points) of the take-up difference between the two groups—a measurable amount, but not nearly enough to explain the full take-up difference of roughly 13 percentage points.

Price differences across treatment and control groups

Before turning to behavioral factors that may explain the pattern of take-up observed, it is important to address how much of the explanation could simply be due to the difference in prices between the two products. It is possible that farmers simply did not place a very high value on the insurance they were offered, and they had a very high price elasticity of demand for credit. They may not have placed a high value on the insurance if they realized that rainfall recorded at the reference weather station was not highly correlated with rainfall on their own plot (i.e., basis risk was very high), or perhaps simply because they did not trust the insurance company to pay the loan on their behalf in case of drought. Low valuation of insurance, in combination with very high price elasticity, could have caused low take-up of the insured loan.

While this explanation could explain some modest portion of the decline, we believe that the price difference cannot be the full explanation. A decline in take-up of 13

percentage points (from a base of 33.0%) is very large (this is a 39.4% decline from the uninsured loan take-up rate). At the same time, the price increase due to insurance is relatively small—roughly 11.3% for the combined groundnut and maize packages. These magnitudes imply that the price elasticity of credit demand for farmers would have to be 3.49 for the full decline in take-up to be purely due to the price difference (39.4% divided by 11.3%). This would be an extremely large price elasticity.

Other potential factors

It is also possible that being offered the insured loan may have primed farmers to weigh risk considerations more highly in their adoption decision. In many settings psychologists have found that “priming” by highly local and temporary influences can have large effects on decision making. For example, Bornstein (1989) and Zajonc (1968) find that mere exposure can increase affinity for certain things, even if the exposure is subliminal. Bettman and Sujan (1987) found that subjects were more receptive to advertisements emphasizing a camera’s creative potential when they were primed with words related to “creativity.”

In the experiment, farmers could have been encouraged to worry more about the riskiness of the hybrid seed investment when the insured loan was explained to them, reducing their adoption rates. When farmers were offered the uninsured loan, there was no discussion of weather risk, and farmers were simply given information on the loan terms. By contrast, the offer of the insured loan by its nature required a discussion of the risk of crop loss due to weather, as a motivation for the insurance. The increased salience

of weather risk may have made farmers in insured loan treatment weigh risk more heavily in their decision to take up the hybrid seed loan (in comparison to the uninsured loan farmers). This increased perception of risk could have more than offset the risk-reduction effect of insurance, and could help explain lower adoption of the insured loan.¹⁰

An additional possible explanation is that farmers could have perceived the default costs as different across the two products. When offered the uninsured loan, farmers may have thought that with some positive probability NASFAM would not actually impose substantial penalties if they defaulted on the loan. When the insured loan was offered to farmers, by contrast, there could have been greater emphasis on the fact that the lender was going to impose penalties for nonpayment (even if the loan were to be forgiven in the event of poor rainfall). Farmers could therefore have perceived higher costs for default in the credit plus insurance product, leading that product to have lower take-up.

6. Conclusion

A large body of theory and empirical work in development economics argues that technology adoption (and income-maximizing production choices more generally) may be hindered when returns are risky and insurance or other financial markets are imperfect. This paper reports the results from an experimental study that tested whether reducing risk fosters technology adoption. Nearly 800 maize and groundnut farmers in Malawi

¹⁰ It is also possible that farmers may have been uncertain about the risk characteristics of the hybrid seeds, and took the fact that they were offered insurance as a signal from NASFAM that the seeds were riskier than they would have thought otherwise. Lower take-up of the credit plus insurance product would then be a rational (not behavioral) response.

(where by far the dominant source of production risk is the level of rainfall) were offered credit to purchase high-yielding hybrid maize and groundnut seeds in advance of the planting season. Farmers were randomized into two groups that differed in whether the loan was insured against poor rainfall. Take-up was 33.0% for farmers who were offered the uninsured loan. Contrary to expectations, take up was lower, by 13 percentage points, among farmers offered insurance with the loan.

These surprising results help underscore the difficulties inherent in designing effective approaches to reducing the consequences of environmental risks for farmers so as to encourage adoption of income-raising technologies. We provide suggestive evidence that reduced take-up of the insured loan was due to the high cognitive cost of evaluating the insurance: insured loan take-up was positively correlated with farmer education levels. By contrast, take-up of the uninsured loan was uncorrelated with farmer education. This suggests that marketing efforts devoted to reducing the complexity of the insurance from the farmer perspective can help ease the acceptance of such insured or contingent loans. However, a number of other additional factors may have also contributed to lower take-up of the insured loan, and we view investigation of such factors as important avenues for future research.

Appendix A: A Simple Model of Technology Adoption¹¹

Imagine a farmer that can grow a crop using either traditional or hybrid seeds. Output from traditional seeds is Y_T . Hybrid seeds have higher average yields but are riskier: Y_H with probability p and Y_L with probability $1-p$. In addition, the seeds are costly, so assuming no liquid wealth, the farmer needs to borrow from a bank to be able to purchase them. Assume that the bank offers a standard debt contract (uninsured loan) at interest rate r and that the cost of the hybrid seeds is C .

In this case, when traditional seeds are planted, consumption is simply $c_N = Y_T$, where the subscript N denotes no adoption of hybrid seeds. In contrast, if the farmer decides to adopt the hybrid seeds, then consumption is $c_i = Y_i - R$, $i = H, L$ where $R = (1+r)C$ is the amount to be repaid to the bank.

Suppose now that banks offer a bundle of credit with rainfall insurance (insured loan). Rainfall can take on two values, low rain l and high rain h , with a probability of high rain of q . Let ρ be the correlation between rainfall and income.¹² Using the definition of correlation, and letting $\varepsilon = \rho\sqrt{p(1-p)q(1-q)}$, we can write the joint probabilities of income and rainfall as $\Pr(Y_H, h) = pq + \varepsilon$, $\Pr(Y_H, l) = p(1-q) - \varepsilon$, $\Pr(Y_L, h) = (1-p)q - \varepsilon$ and $\Pr(Y_L, l) = (1-p)(1-q) + \varepsilon$.

If rainfall is low, the insurance pays out the principal and interest, which now includes the cost of the hybrid seeds C and the insurance premium π . Thus,

$$R^I = (1+r)(C + \pi) \text{ where the premium is simply } \pi = \frac{1-q}{q}C \text{ assuming it is priced fairly.}$$

Combining both expressions, we can write the amount to be repaid under the insured loan as a function of the uninsured loan amount to be repaid, yielding $R^I = \frac{R}{q}$.

For simplicity, we now set the probabilities to $p=q=1/2$. In this case, expected consumption if the insured loan is taken, can be written as $c_H^I = Y_H - (1+\rho)R$ if high output is realized and $c_L^I = Y_L - (1-\rho)R$ in the case of low output. Notice that without basis risk, that is, when $\rho=1$, no repayment is due when Y_L is realized.

Assume that the farmer has expected mean-variance preferences $E[U(c)] = E(c) - \gamma V(c)$. We now solve for the coefficient of risk aversion $\hat{\gamma}$ that leaves the farmer indifferent between adopting the hybrid seeds (and therefore borrowing) without insurance and using the traditional seeds. If the farmer's coefficient of risk aversion satisfies $\gamma \leq \hat{\gamma}$, the farmer will adopt the hybrid seeds, otherwise, he or she will prefer to use the traditional ones. The cutoff risk aversion coefficient is given by

$$\hat{\gamma} = \frac{2[Y_L + Y_H - 2(Y_T + R)]}{(Y_H - Y_L)^2}$$

¹¹ Chris Ahlin provided very valuable suggestions on simplifying the model.

¹² Technically, ρ is the maximum feasible correlation coefficient given p and q . Because income and rainfall are assumed binary variables, unless $p=q$ (as we later do), the two variables cannot be perfectly correlated.

This coefficient $\hat{\gamma}$ is decreasing in income variability $Y_H - Y_L$, so that the higher income variability is, the less likely are farmers to adopt the hybrid seeds. The analogous cutoff coefficient $\hat{\gamma}^I$ for the insured loan is:

$$\hat{\gamma}^I = \frac{2[Y_L + Y_H - 2(Y_T + R)]}{(Y_H - Y_L - 2\rho R)^2 + 4R^2(1 - \rho^2)}.$$

This coefficient $\hat{\gamma}^I$ is still decreasing in income variability $Y_H - Y_L$ but is also increasing in the correlation coefficient ρ . Thus, the lower the basis risk (the higher ρ is), the more likely are farmers to adopt the hybrid seeds.

We are now interested in determining under what conditions will farmers prefer the insured loan to the uninsured one. In other words, when will $\hat{\gamma}^I > \hat{\gamma}$ arise?

Proposition 1. *If $\rho > \frac{R}{Y_H - Y_L}$, then $\hat{\gamma}^I > \hat{\gamma}$ $\hat{\gamma}^I = \hat{\gamma}$ if $\rho = \frac{R}{Y_H - Y_L}$ and $\hat{\gamma}^I < \hat{\gamma}$ if*

$$\rho < \frac{R}{Y_H - Y_L}.$$

Proof: It follows trivially from the expressions of $\hat{\gamma}^I$ and $\hat{\gamma}$ above.

Proposition 1 suggests that as long as the correlation between rainfall and income is large enough, the insured loan offers some consumption smoothing across the two states and thus, there could be farmers that would prefer to grow the traditional seeds if offered an uninsured loan but would adopt the hybrid seeds if offered an insured one.

Figure 4 plots the cutoff coefficient of risk aversion $\hat{\gamma}$ and $\hat{\gamma}^I$ as a function of income variability $Y_H - Y_L$. For any combination of risk aversion coefficient and income variability north-east of the indifference curves, the farmer will decide not to adopt hybrid seeds and will grow instead the traditional seeds. If the correlation between rainfall and income is large enough ($\rho > \frac{R}{Y_H - Y_L}$), the indifference curve $\hat{\gamma}^I$ lies north

east of the indifference curve $\hat{\gamma}$. In contrast, when the correlation is low and even negative, the indifference curve $\hat{\gamma}^I$ lies south west of the indifference curve $\hat{\gamma}$, as all farmers prefer the uninsured loan to the insured one. When the correlation is negative, basis risk is too large because the farmer is asked to repay more whenever income is low at Y_L than when income is high at Y_H . Thus, the consumption variability is higher with insurance than without.

To sum up, Proposition 1 suggests that if the basis risk is low, providing a bundle of credit with insurance should increase adoption among risk-averse farmers.

Extension of Model to Complexity and Ambiguity Aversion

We refer to complexity as the extent to which a given farmer fails to understand the insurance contract bundled with credit. While complexity can be modeled in many

ways, we assume that it affects the perceived basis risk or correlation between income and rainfall ρ . To keep matters simple, we assume that the perceived correlation between rainfall and income is $\tilde{\rho} = \rho(1 - \phi) - \phi$, where the parameter ϕ varies from 0 to 1 and measures the degree of complexity. When $\phi = 0$ there is no complexity so that the farmer's perception of basis risk coincides with the actual basis risk $\tilde{\rho} = \rho$, but when $\phi = 1$ there is maximum complexity and the perceived basis risk is also maximum $\tilde{\rho} = -1$, regardless of the actual correlation ρ .

Under complexity, the perceived consumption bundles under the two states of nature are

$$c_H^I = Y_H - ((1 + \rho)(1 - \phi))R \text{ and } c_L^I = Y_L - (1 + \phi - \rho(1 - \phi))R.$$

Thus, the higher the complexity, the higher the basis risk perceived by the farmer and as a result, the less desirable the insured loan will appear to be.

Appendix B: Variable definitions

Data are from the Malawi Technology Adoption and Risk Initiative (MTARI) farm household survey in September-October 2006. All variables refer to respondent or respondent's household.

Take-up equal to 1 if respondent signed up for hybrid seed loan, 0 otherwise.

Treatment equal to 1 if respondent offered insured loan, 0 if offered uninsured loan.

Risk tolerance is self-reported on 0-10 scale: higher indicates greater tolerance for risk in trying new crop varieties.

House quality is the first principal component of several binary asset variables. Variables are defined for housing construction materials, water source, and electricity source. In general, variables are defined such that "1" represents a higher standard of living than "0." The binary asset variables used in this analysis are for brick housing construction, non-earthen floors, metal roofs, and running water (including water piped into the residence and water from a public tap). Additionally, we use two variables that are exceptions to the rule of "1" representing a higher standard of living. The first of these is for well water, as opposed to either running water or unimproved water sources. The second is for gas lighting, as opposed to either electricity or solar power, or firewood, candles, or no lighting.

Net income is computed as the sum of farm profits and non farm income, and is reported in Malawi kwachas (MK). Farm profits are the monetary value of crops produced less the monetary cost of farming inputs. Farming inputs include irrigation, fertilizer, chemical insecticides, manure or animal penning, hired equipment such as tractors, and hired manual labor and oxen labor. Information on farm revenue and expenditure was collected for each plot; total farm profits are computed as the sum of profits over all plots farmed by an individual. Non farm income includes wages from agricultural labor (on other peoples' farms); wages from non-agricultural labor; wages or in-kind wages from public works programs; remittances; benefits from government programs; pension income; and other sources of income. Information on these sources of

income was collected for each respondent, and added to farm profits to compute total net income.

Drop in income due to drought equals 1 if the household has suffered a negative income shock due to drought over the past 5 years.

Trust in insurance company is self-reported on a 0-10 scale (higher values indicate greater trust in insurance companies).

Binary variables were generated to allow flexible functional form estimates of the impact of *education*, *net income* and *land ownership* and are computed as follows. For education, the first quintile includes those with 0 to 2 years of schooling; the second quintile includes those with 3 or 4 years of schooling; the third quintile includes those with 5, 6, or 7 years of schooling; the fourth quintile includes those with 8 years of schooling; and the fifth quintile includes those with 9 to 15 years of schooling. For income, the quintile breakdown is as follows: the first quintile includes those with net incomes of between -215,343 MK and 550 MK; the second quintile includes those with net incomes between 600 MK and 5,380 MK; the third quintile includes those with incomes between 5,400 MK and 13,000 MK; the fourth quintile includes those with incomes between 13,218 MK and 27,300 MK; and the fifth quintile includes those with incomes between 27,500 MK and 3,712,300 MK. Finally, five dummy variables for land ownership represent holdings of 0 to 3 acres; 3.25 to 4 acres; 4.25 to 6 acres; 6.25 to 10 acres; and 10.25 to 108 acres, respectively. Indicator variables for age are binary variables for the following age categories: under age 25, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-60, and 65 and over.

References

Benjamin, Dwayne. 1992. "Household Composition, Labor Markets, and Labor Demand: Testing for Separation in Agricultural Household Models" *Econometrica*, Vol. 60, No. 2, pp. 287-322.

Bertrand, Marianne, Sendhil Mullainathan, and Eldar Shafir, "Behavioral Economics and Marketing in Aid of Decision-Making among the Poor," *Journal of Public Policy and Marketing*, forthcoming.

Besley, Timothy and Anne Case (1993). "Modeling Technology Adoption in Developing Countries." *American Economic Association Paper and Proceedings*, Vol. 83(2), May, pp. 396-402.

Besley, Timothy and Anne Case (1994). "Diffusion as a Learning Process: Evidence from HYV Cotton," Princeton University Working Paper.

Bettman, J. R., & Sujan, M., "Effects of framing on evaluation of comparable and non-comparable alternatives by expert and novice consumers," *Journal of Consumer Research*, 14, 1987, p. 141-154.

Binswanger, Hans P. and Donald A. Sillers, 1983. "Risk Aversion and Credit Constraints in Farmers' Decision-Making: A Reinterpretation" *Journal of Development Studies* 20, 5-21.

Bornstein, R.F., "Exposure and effect: Overview and meta-analysis of research, 1968-1987," *Psychological Bulletin*, 106, 1989, p. 265-289.

Boucher, Stephen, Michael R. Carter, Catherine Guirkinger. 2006. "Risk Rationing and wealth Effects in Credit Markets" Working Paper No 05-010, Department of Agricultural and Resource Economics, UC-Berkeley.

Chaudhuri, Shubham and Theresa Osborne, 2002. "Financial Market Imperfections and Technical Change in a Poor Agrarian Economy" Working Paper, European University Institute, Florence, Italy.

Conley, Timothy and Christopher Udry, "Learning About a New Technology: Pineapple in Ghana," mimeo, Yale University, July 2005.

Dercon, Stefan and Luc Christiaensen, "Consumption risk, technology adoption and poverty traps: evidence from Ethiopia," World Bank Policy Research Working Paper 4257, June 2007.

Dowd, Kevin, 1992. "Optimal Financial Contracts" *Oxford Economic Papers* 44, pp. 672-693.

Duflo, E., Gale, W., Liebman, J., Orszag, P., and Saez, E., "Saving incentives for low- and middle-income families: evidence from a field experiment with H&R Block," NBER Working Paper No. 11680, October 2005.

Duflo, Esther, Michael Kremer and Jonathan Robinson, "Understanding Technology Adoption: Fertilizer in Western Kenya: Evidence from Field Experiments," mimeo, MIT, Harvard University, and Princeton University, April 2006.

Evenson, Robert (1974). "International Diffusion of Agrarian Technology." *Journal of Economic History*, Vol. 34(1), March, pp. 51-73.

Evenson, R. and L. Westphal (1995). "Technological Change and Technology Strategy." *Handbook of Development Economics*. J. Behrman and T. N. Srinivasan. Amsterdam, North-Holland. 3A: 2209-2300.

Feder, Gershon & Just, Richard E & Zilberman, David, 1985. "Adoption of Agricultural Innovations in Developing Countries: A Survey," *Economic Development and Cultural Change*, University of Chicago Press, vol. 33(2), pp. 255-98.

Foster, A. and M. Rosenzweig (1995) "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture" *Journal of Political Economy*, Vol. 103(6), p 1176-1209.

Goldman, Abe (1993). "Agricultural Innovation in Three Areas of Kenya: Neo-Boserupian Theories and Regional Characterization." *Economic Geography*, Vol. 69(1), January, pp. 44-71.

Griliches, Zvi (1957). "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, Vol. 25(4), October, pp. 501-522.

Just, Richard E. and David Zilberman (1983). "Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture." *Oxford Economic Papers*, Vol. 35(2), July, pp. 307-328.

Liebman, J.B. & Zeckhauser, R.J., "Schmeduling," working paper, Harvard University, 2004.

Moulton, Brent, "Random Group Effects and the Precision of Regression Estimates," *Journal of Econometrics*, 32, 3, August 1986, p. 385-397.

Munshi, Kaivan, "Technology Diffusion," in Kaushik Basu, ed., *Oxford Companion to Economics in India*. New Delhi: Oxford University Press, forthcoming.

Munshi, Kaivan, "Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution," *Journal of Development Economics*, 73 (1), 2004, pp. 185-215.

Rogers, Everett M., *The Diffusion of Innovations*, 4th Edition. New York: Simon & Schuster, 1995.

Simtowe, Frankin, “Can risk-aversion explain part of the non-adoption puzzle for hybrid maize? Empirical evidence from Malawi,” *Journal of Applied Sciences*, 6, 7, 2006, p. 1490-1498.

Simtowe, Franklin and Manfred Zeller, “The impact of access to credit on the adoption of hybrid maize in Malawi: an empirical test of an agricultural household model under credit market failure,” Munich Personal RePec Archive (MPRA) Paper No. 45, September 2006.

Smale, Melinda, Paul W. Heisey, and Howard D. Leathers, “Maize of the Ancestors and Modern Varieties: The Microeconomics of High-Yielding Variety Adoption in Malawi,” *Economic Development and Cultural Change*, 43, 2, January 1995, p. 351-368.

Smale, Melinda and Thom Jayne, “Maize in Eastern and Southern Africa: ‘Seeds’ of Success in Retrospect,” International Food Policy Research Institute, EPTD Discussion Paper No. 97, January 2003.

Wessels, W. (2001) “Proposal to Release DK8051 and DK8031 and DK8041”, Monsanto South Africa.

World Bank, “Malawi Poverty and Vulnerability Assessment 2006: Investing in Our Future,” draft, June 2006.

Zajonc, R.B., “Attitudinal effects of mere exposure,” *Journal of Personality and Social Psychology Monographs*, 9, 2, 1968, p. 1-27.

Figure 1. Malawi study areas

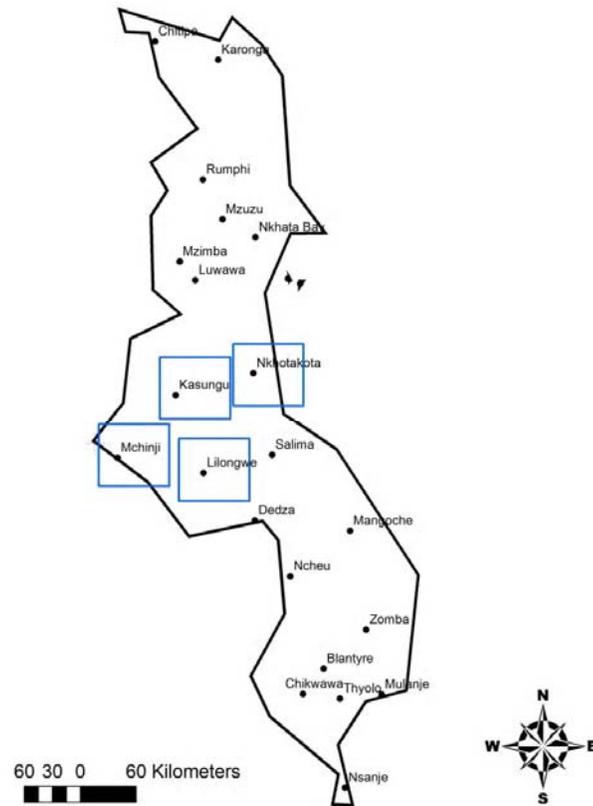


Figure 2. Farmer locations in central Malawi study areas

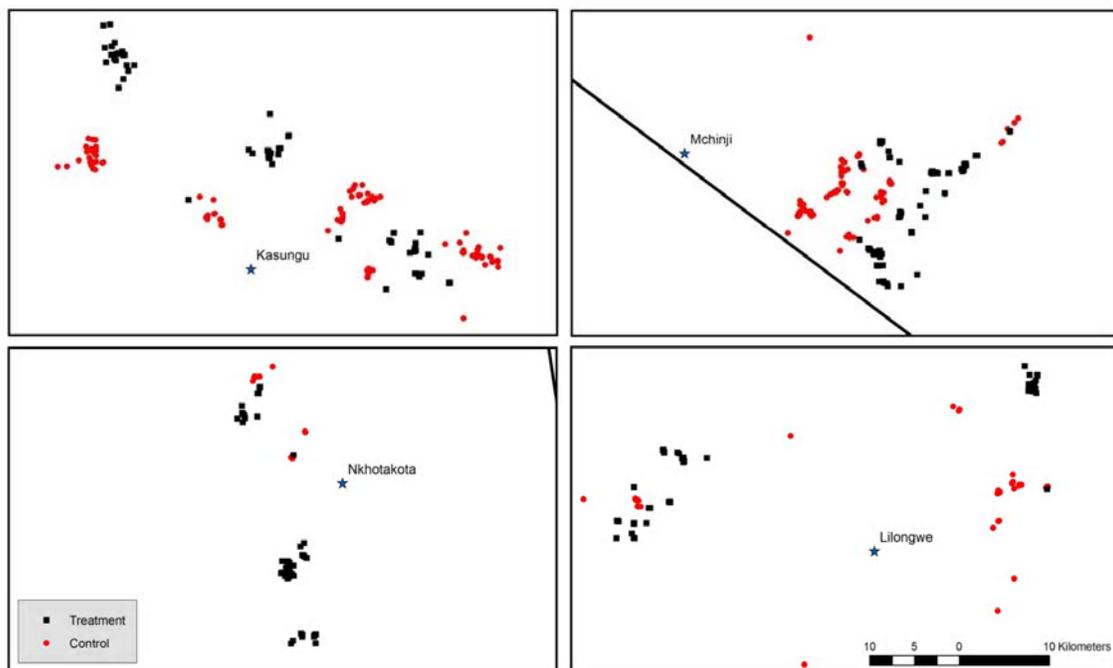


Figure 3. Insurance policy

The rainfall insurance policy divides the cropping season into three phases. The graph below shows how rainfall during the phase translates into the insurance payout for one phase.

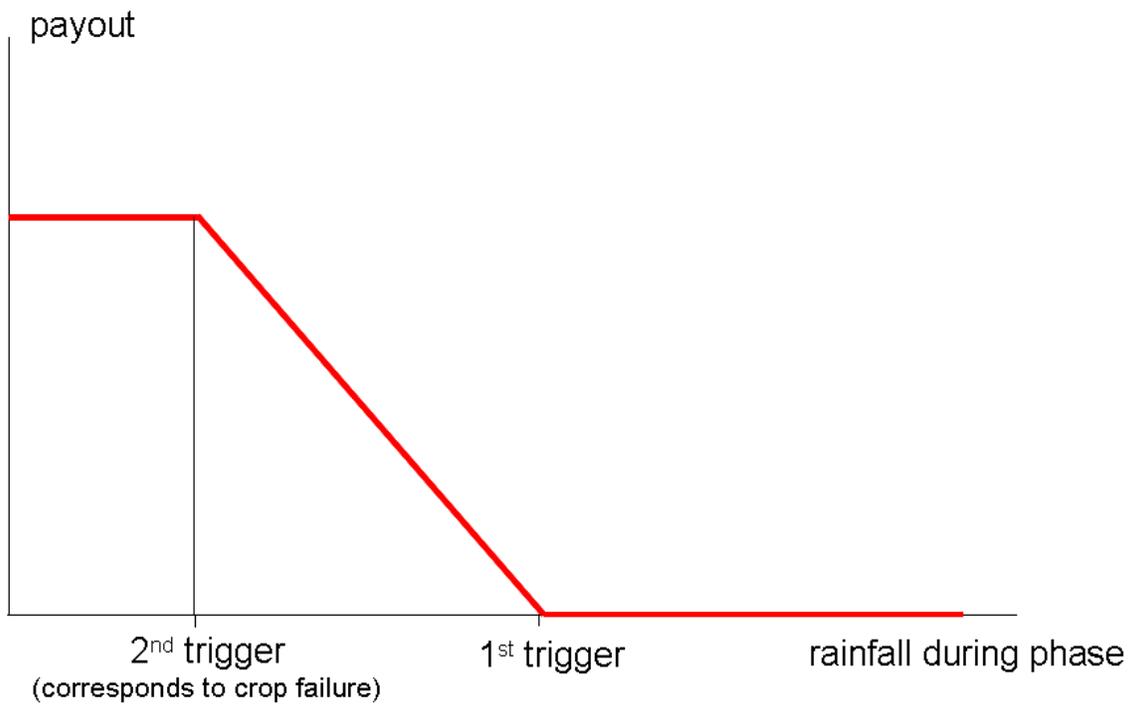


Figure 4. Adoption Decision as Function of Risk Aversion Coefficient

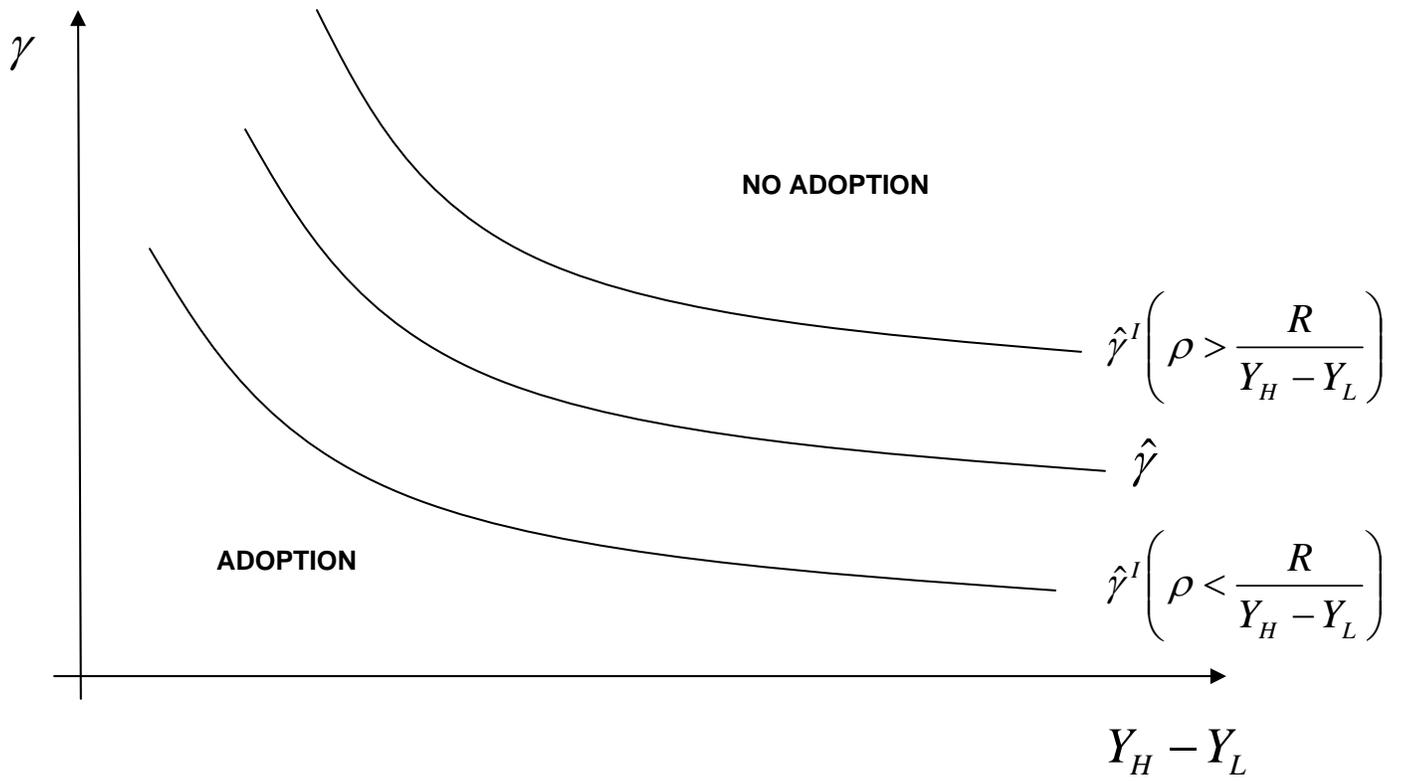


Table 1: Summary statistics

September - October 2006

<u>Variable</u>	<u>Mean</u>	<u>Std. Dev.</u>	<u>Min.</u>	<u>10th pct.</u>	<u>Median</u>	<u>90th pct.</u>	<u>Max.</u>	<u>Num. Obs.</u>
Take-up (indicator)	0.26	0.44	0.00	0.00	0.00	1.00	1.00	836
Treatment (indicator)	0.50	0.50	0.00	0.00	0.00	1.00	1.00	787
Female (indicator)	0.44	0.50	0.00	0.00	0.00	1.00	1.00	1,086
Household is female headed (indicator)	0.12	0.33	0.00	0.00	0.00	1.00	1.00	1,087
Years of schooling	5.28	3.55	0.00	0.00	5.00	10.0	15.0	1,072
Risk tolerance	7.24	3.39	0.00	0.00	9.00	10.0	10.0	1,064
Age	41.7	12.9	13.0	26.0	40.0	59.0	92.0	1,074
Land owned	7.15	7.81	0.00	2.00	5.00	13.0	108	1,088
House quality	0.00	1.27	-0.91	-0.85	-0.73	2.59	3.10	1,087
Net income (MKs 100,000)	0.27	1.36	-2.15	-0.01	0.09	0.47	37.123	1,087
Drop in income due to drought (indicator)	0.32	0.47	0.00	0.00	0.00	1.00	1.00	1,088
Trust in insurance company	5.07	3.98	0.00	0.00	5.00	10.0	10.0	709

Notes -- Data are from the Malawi Technology Adoption and Risk Initiative (MTARI) farm household survey in September - October 2006. All variables refer to respondent or respondent's household. See Appendix B for definition of variables.

Table 2: Differences in means, treatment vs. control group

September - October 2006

<u>Variable</u>	<u>Treatment mean</u>	<u>Control mean</u>	<u>Difference</u>	<u>p-value</u>
Female (indicator)	0.443	0.445	-0.002	0.975
Household is female headed (indicator)	0.125	0.119	0.006	0.852
Years of schooling	4.919	5.760	-0.841*	0.062
Risk tolerance	7.368	7.436	-0.068	0.779
Age	40.936	40.357	0.579	0.759
Land owned	6.440	7.759	-1.319	0.117
House quality	-0.144	0.087	-0.231	0.228
Net income (MKs 100,000)	0.202	0.316	-0.114	0.364
Drop in income due to drought (indicator)	0.333	0.305	0.028	0.499
Trust in insurance company	5.05	5.062	-0.012	0.974

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes -- Table presents means of key variables for treatment group (farmers offered insured loan) and control group (farmers offered uninsured loan) in September - October 2006, prior to treatment. P-value is for F-test of difference in means across treatment and control groups, and accounts for clustering at level of 32 localities. See Appendix B for definition of variables.

Table 3: Impact of insurance on take-up of loan for hybrid seeds

(Ordinary least-squares estimates)

Dependent variable: Respondent took up loan for November 2006 planting season

	(1)	(2)	(3)	(4)	(5)
Treatment indicator	-0.154 [0.109]	-0.141 [0.082]*	-0.132 [0.082]	-0.128 [0.074]*	-0.134 [0.076]*
Female (indicator)			-0.027 [0.031]	-0.036 [0.034]	-0.039 [0.035]
Household is female headed (indicator)			0.038 [0.053]	0.054 [0.053]	0.049 [0.051]
Years of schooling			0.010 [0.005]*		
Age			0.002 [0.001]		
Land owned			0.001 [0.002]		
House quality			0.016 [0.018]	0.015 [0.018]	0.016 [0.017]
Net income (MKs 100,000)			0.009 [0.014]		
Region fixed effects		Y	Y	Y	Y
Indicators for 5-year age categories				Y	Y
Land quintile indicators				Y	Y
Income quintile indicators				Y	Y
Education quintile indicators				Y	
Mean dependent variable	0.253	0.253	0.253	0.253	0.253
Observations	787	787	787	783	783
R-squared	0.03	0.13	0.15	0.17	0.17

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes -- Standard errors clustered by 32 localities in square brackets. Dependent variable equal to 1 if respondent took up loan for November 2006 planting season, and 0 otherwise. Treatment indicator is 1 if loan is insured (respondent is in treatment group), 0 otherwise (respondent is in control group). Region fixed effects are for four study regions (Lilongwe North, Kasungu, Mchinji, and Nkhotakota). See Appendix B for definition variables and quantile indicators.

Table 4: Determinants of take-up in treatment and control groups

(Ordinary least-squares estimates)

Dependent variable: Respondent took up loan for November 2006 planting season

	Treatment group (insured loan)				Control group (uninsured loan)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of schooling	0.014 [0.006]**	0.014 [0.005]**	0.014 [0.005]**	0.009 [0.005]*	0.016 [0.009]	-0.001 [0.008]	-0.001 [0.008]	0.002 [0.008]
Risk tolerance			0.008 [0.006]	0.008 [0.007]			0.015 [0.004]***	0.015 [0.004]***
Female (indicator)				-0.008 [0.051]				-0.021 [0.047]
Household is female headed (indicator)				0.022 [0.062]				0.022 [0.090]
Age				0.001 [0.002]				0.004 [0.002]**
Land owned				0.002 [0.003]				0.000 [0.002]
House quality				0.024 [0.031]				0.010 [0.022]
Net income (MKs 100,000)				0.079 [0.048]				0.003 [0.011]
Drop in income due to drought (indicator)				-0.086 [0.050]				-0.070 [0.040]*
Trust in insurance company				0.010 [0.006]				0.003 [0.006]
Region is Lilongwe North (indicator)		0.103 [0.203]	0.104 [0.203]	0.128 [0.192]		-0.498 [0.082]***	-0.497 [0.079]***	-0.484 [0.078]***
Region is Mchinji (indicator)		0.000 [0.096]	-0.006 [0.097]	-0.006 [0.091]		-0.516 [0.066]***	-0.513 [0.061]***	-0.532 [0.054]***
Region is Nkhhotakota (indicator)		0.254 [0.157]	0.258 [0.157]	0.246 [0.156]		-0.404 [0.096]***	-0.408 [0.091]***	-0.426 [0.092]***
Mean dependent variable	0.176	0.176	0.176	0.176	0.330	0.330	0.330	0.330
Observations	393	393	393	393	394	394	394	394
R-squared	0.02	0.07	0.08	0.12	0.01	0.27	0.29	0.310

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes -- Standard errors clustered by localities in square brackets. Dependent variable equal to 1 if respondent took up loan for November 2006 planting season, and 0 otherwise. Omitted region indicator is for Kasungu. See Appendix B for definition of var