Uptake and evaluation of innovative insurance embedded credit for promoting resilience and livelihoods for smallholder farmers in Kenya

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Formative evaluation report

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About this formative study

This formative evaluation was submitted in partial fulfilment of the requirements of grant TW13.I.1051 awarded under Agricultural Insurance Evidence Programme. This version of the report is technically sound and 3ie is making it available to the public in this final report version as it was received. No further work has been done.

The 3ie technical quality assurance team comprises Bidisha Barooah, Benjamin Wood, Stuti Tripathi and Deeksha Ahuja, with overall technical supervision by Marie Gaarder.

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1. Introduction

Uninsured risks are a major cause of low agricultural productivity in Kenya. According to Government of Kenya, four consecutive years (2008-2011) of drought amounted to US $12.1 billion in losses, including losses in assets and from disruptions in the economy flow across all sectors. Such severe shocks cannot be financed by the government and donor community alone. Moreover, lack of capital and perceived risks limit farmers' ability to purchase agricultural inputs and access credit, contributing to low agricultural productivity. While rural branches have grown 81% over the last five years and the M-Pesa mobile cash transfer service has increased by 1,000%, banks are still resistant to providing loans to the agricultural sector. With 80% of the population employed in agriculture and 22% of the country's overall GDP derived from agriculture, enhancing agricultural productivity is critical for Kenya.

IFPRI is implementing a market-based, innovative risk management solution in the form of Risk-Contingent Credit (RCC), a social safety net designed to mitigate drought risks for the rural poor and improve farm productivity and livelihood in Kenya. This project is funded by Global Resilience Partnership (http://www.globalresiliencepartnership.org/). RCC is a linked financial product that embeds within its structure an insurance protection which, when triggered, offsets loan payments due to the lender providing a risk-efficient balance between business and financial risks. The triggering event is defined around extreme drought risks with a measurable and impactful effect on crop yields. The underlying risk is captured through the development of a satellite-derived drought index that integrates environmental key variables (e.g. rainfall, vegetation and soil moisture) based on state-of-the-art remote sensors. We develop the drought index by estimating a response function of household-level historical crop yields with composite remote sensing indexes of rainfall, vegetation and soil moisture. The accurate estimation of the response function on the basis of actual yield experience by farmers in the area will reduce the design related basis risk significantly and will increase the value proposition of the product.

Because the insurance component of RCC substitutes for collateral, it is more financially inclusive than conventional credit products. Thus RCC can bring risk-rationed farmers (who tend not to borrow or borrow less than optimal for fear of losing collateral and falling into a credit-driven poverty trap) into the credit market. This intervention is now implemented by Kenya's largest private sector bank, Equity Bank along with reinsurance offered by SwissRe. In RCC the indemnity from the insurance is applied to the underlying debt obligation or debt service, thereby reducing the probability of default on loans by producers, improving risk bearing ability and trust, enhancing the supply of credit, and facilitating investment and development. It also eliminates the drawbacks of standalone index insurance products by not requiring the farmers to pay premium upfront. The above mentioned rational and structure of insurance embedded credit contributes to high and sustained uptake of RCC by farmers with significant and consequential impacts on various welfare outcomes.

It is important to test if this innovative product can increase the uptake of agricultural risk management instruments by farmers. We will test the approach by Carter (2011), who examined the impacts of bundled credit on financial market deepening and its impacts on farm households, concluding that RCC capitalized the adoption of new technology. Giné and Yang (2009) investigated adoption of an operating loan in Malawi where the payoff was determined by rainfall found low take-up. Karlan *et al.* (2011) investigated the adoption of price-contingent credit in Ghana and found high loan uptake. Finally, Shee and Turvey (2012) showed how risk-contingent instrument can be priced in practice and using simulated field data they concluded that an imbedded price option for pulse crops in India provided downside risk protection for the pulse farmers. Our formative evaluation adds to this body of literature with the unique mechanism of RCC.

The report is organized as follows: the next section would give a context of the RCC intervention in terms of site selection and its geographic and socio-economic characteristics. Section 1.3 describes the RCC intervention and theory of change. Section 1.4 introduces our monitoring plan. The following two sections deal with evaluation questions, design, and methods. Section 1.7 outlines the timeline of this study. Section 1.8 reports the major findings and analysis of the current evaluation, followed by some implications of these study findings. We conclude with major challenges and lessons learned.

2. Context

Machakos County is a semi-arid and hilly terrain area in Eastern province of Kenya. It receives very low annual rainfall of around 700 mm per year with average rainfall in long and short rain seasons being 315 and 266 mm, respectively (Situation Analysis-GOK 2014). Due to this semi-arid climate agriculture is practiced smallholder farmers with maize being the main food crop. The RCC pilot area covers eleven divisions in the Machakos County including Central Machakos, Yathui, Yatta, Masinga, Matungulu, Kalama, Kathiani, Mwala, Kangundo, Ndithini, and Mavoko.

This is a maize growing area, with some intercropping with perennial fruits or other cash crops. Most farms in this area are smallholder farms, with limited resources, and little to no access to credit. It is universally acknowledged by farmers that the primary risk faced are failures in the long and or short rains. While rainfall is variable in the long and short rain periods (October 15th – January 15th, and March 15th -May 15th) the infrequent failure of one or the other, and sometimes both rainfalls causes great hardship, and almost certain default on loans if credit were provided.

Figure 1: Project area: Machako county, Kenya

The household survey collected information on various socioeconomic variables such as demography, agricultural land characteristics, production and inputs, livestock ownership, credit, and risk preference. Below we present household-level summary statistics of average household size, maximum adult years of education, female headed households, average age of household head, number of working age labor, and total land size. Number of working age members in a household are calculated as the number of household member aged between 15 and 64 years. The average household size is 5.44 members and ranges between 1 to 15 members. Maximum adult years of education in the household is about 11 years. About 21 percent households are female headed. The average age of household head is 56.45 years and varies between 22 to 95 years. The average number of working age labor in the household is 3.26. The average household-level land size is 4 acre.

Table 1: Household level summary statistics of key variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Household size	1,170	5.44	2.24	1	15
Max years of education in the household	1,169	11.09	2.77	0	17
Female headed household	1,170	0.21	0.41	0	1
Age of the head	1,123	56.45	13.21	22	95
No. of working age labor	1,170	3.26	1.64	0	11
Total land size (Acre)	1,170	4.00	7.80	0.25	202.5

The household size and maximum adult years of education are further depicted by Sub-County in Figure 2 and 3, respectively. The average household size is the highest in Yatta compared to other 4 Sub-Counties. Regarding maximum adult years of education, Matungulu has the highest number of years compared to other Sub-Counties.

Figure 2: Average household size by Sub-County

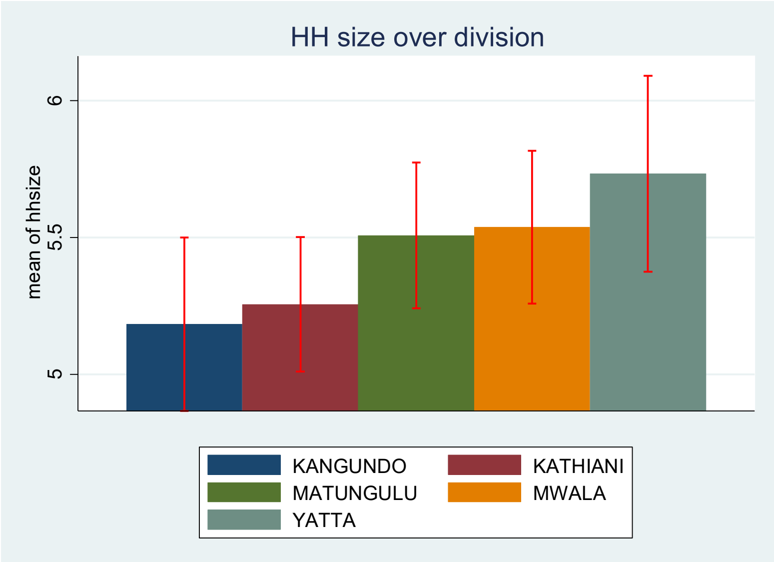
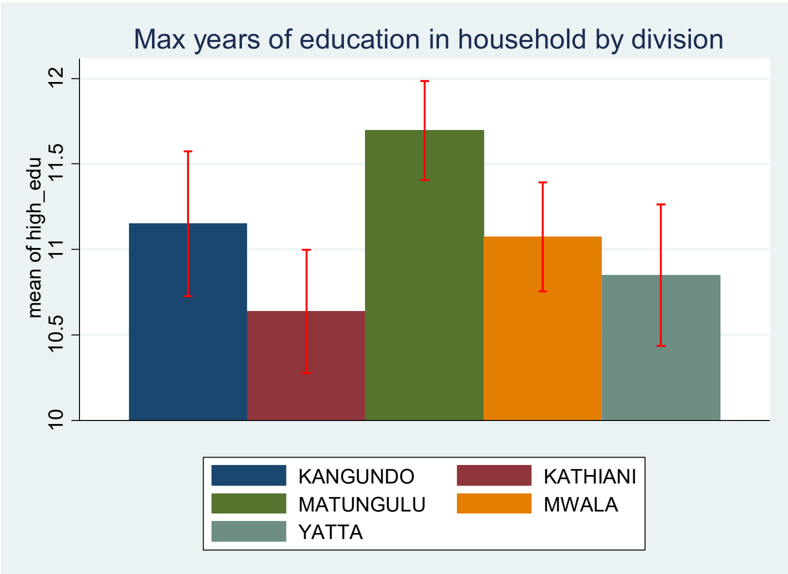


Figure 3: Maximum years of education in household by Sub-County



The summary of agricultural land size is further depicted by Sub-County in Figure 4. On average Yatta has higher average household land size whereas it has lower maize productivity compared to other Sub-Counties.

Figure 4: Average land size by Sub-County

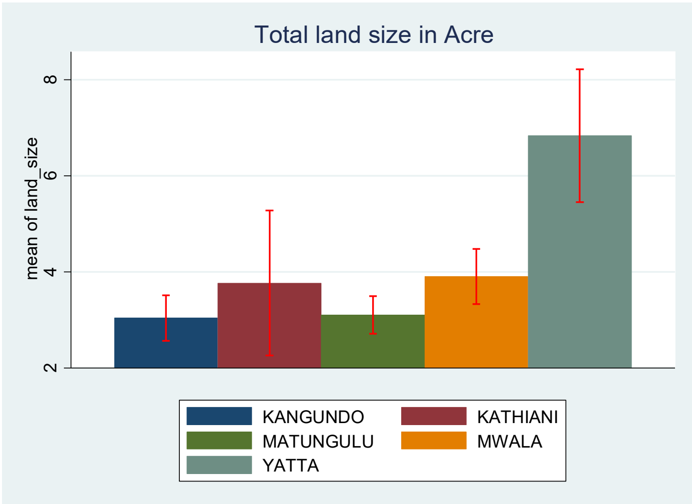


Figure 5: Average yield (kg/acre) of maize by Sub-County

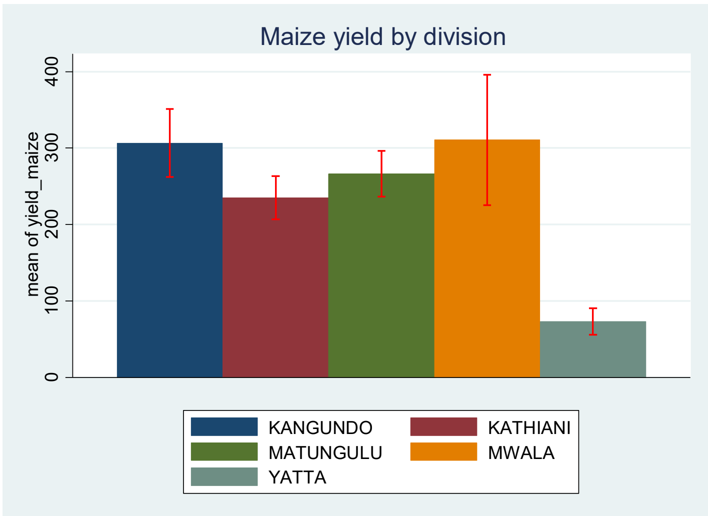
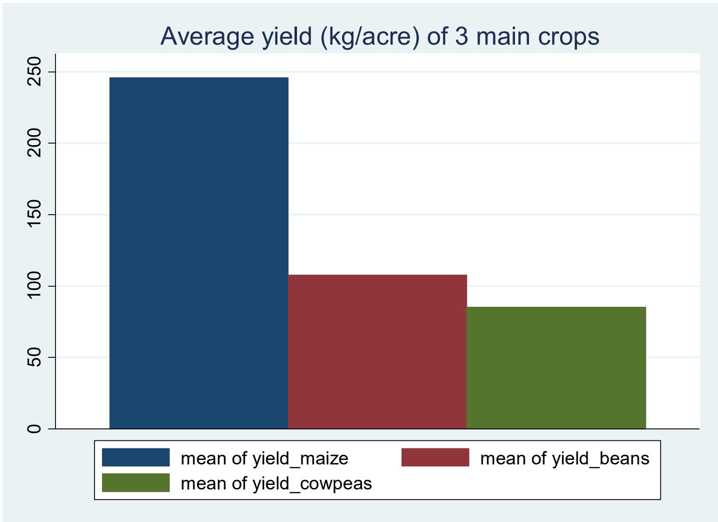
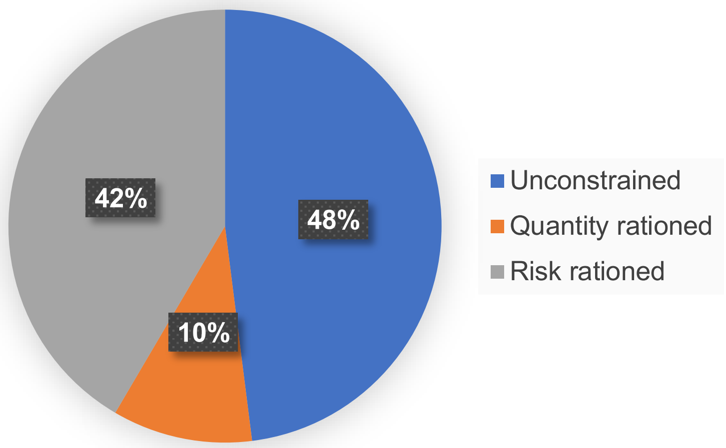


Figure 6: Average yield (kg/acre) of 3 main crops



From the project baseline household survey we found that almost half of the sample household are credit rationed. Interestingly, 42% of the household are risk-rationed who voluntarily withdraw themselves from the credit market. RCC mechanism is very relevant for this population because RCC tool can bring these population into the credit market by acting as a substitutes for collateral.

Figure 7: Credit rationing status of study household (Source: project household survey)



3. Intervention description and theory of change

IFPRI is implementing a market-based, innovative insurance embedded credit solution in the form of Risk-Contingent Credit (RCC), a social safety net that could mitigate drought related production risk and can also provide access to credit for agriculture. RCC is an insurance-linked financial product which, when triggered, offsets loan payments due to the lender. The triggering event is defined around measurable covariate risks of a catastrophic nature such as drought that affect crop yields. The underlying risk is captured through the development of a satellite-derived drought index that integrates environmental key variables (e.g. rainfall, vegetation and soil moisture) based on state-of-the-art remote sensors. We develop the drought index by estimating a response function of household-level historical crop yields with composite remote sensing indexes of rainfall, vegetation and soil moisture.

Below we provide a brief description of RCC and how it can protect farmers from drought related production risk. In Figure 8 the upper graph shows loan repayment and the lower graph illustrates the underlying insurance payout in relation to worsening conditions (to the left). If the underlying risk (weather-related) worsens and crosses a certain threshold, or trigger, the total repayment obligation of a farmer falls linearly with the difference deposited directly into the borrowers loan account at the bank by the insurer. On the other hand, if the underlying risk is not triggered the loan has to be repaid at the risk-contingent interest rate (which will be higher than the market base rate). RCC has therefore the unique characteristic that even though farmers have to pay a risk premium during normal circumstances, they are insured against adverse circumstances. RCC is designed with an actuarially fair interest rate that is interlinked with the targeted underlying risk.

Figure 8: Schematic Illustration of Risk-Contingent Credit (RCC)

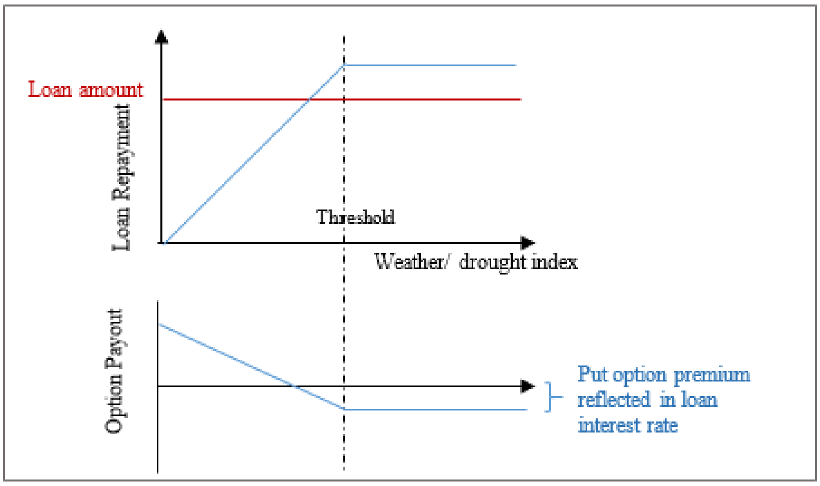
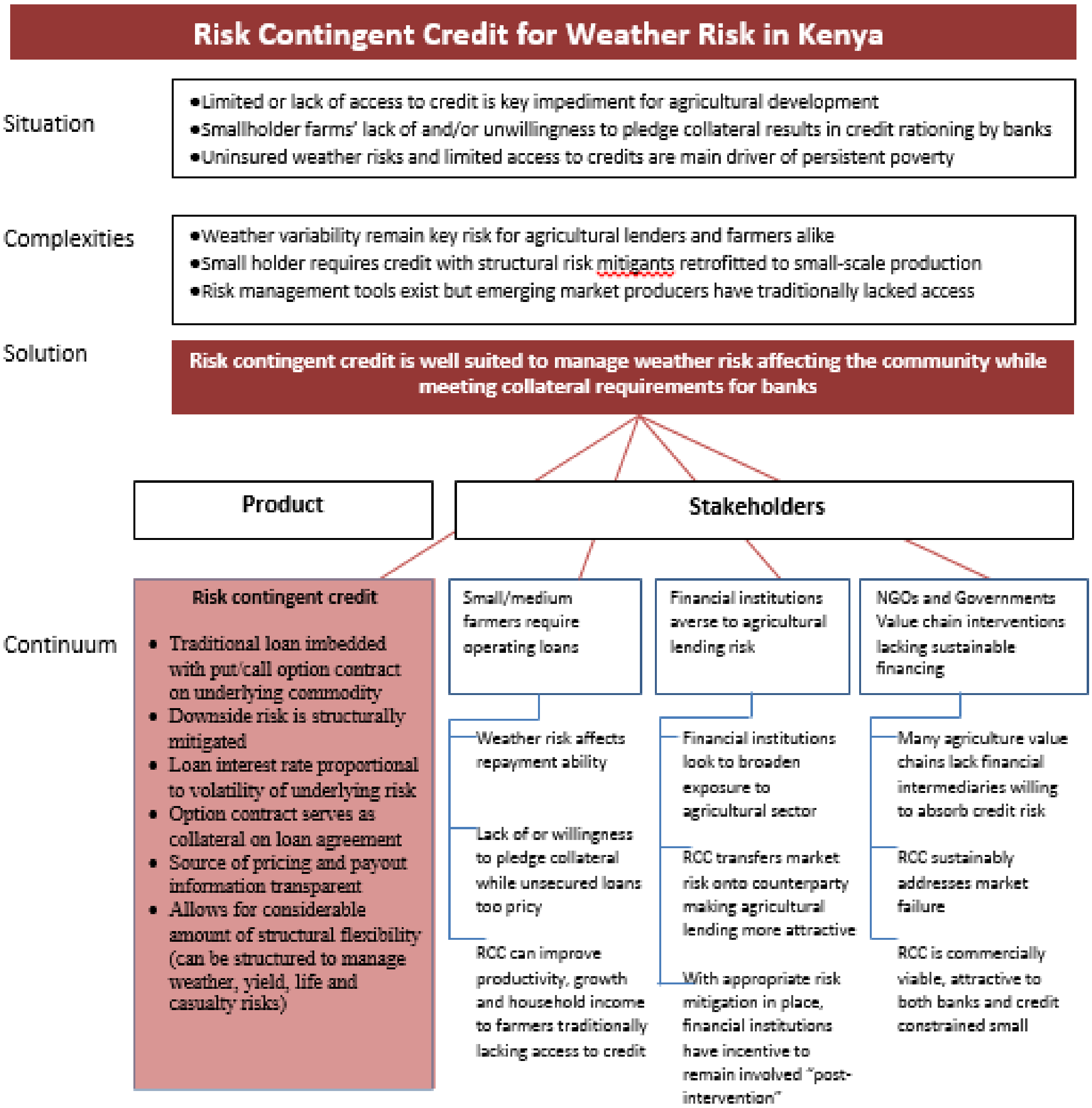


Figure 9: RCC Business Model Schematics



Our main national partners are Equity Bank Kenya and Agri-Food Economics Africa Limited of Kenya. We have worked together on creating awareness about agricultural risk management strategies, capacity building and outreach, and development and implementation of suitable RCC products. The RCC business model (Figure 9) involves individual farmers, commercial financial institutions (local banks), research institutions and an international reinsurer. This intervention is currently implemented by Kenya's largest private sector bank, Equity bank along with reinsurance offered by SwissRe.

The planned theory of change of our project is presented in Figure 10. The question here is: Does RCC improve the production strategies and welfare of smallholder maize and wheat farmers? The theory of change diagram links actual needs to inputs, expected outputs, outcomes and long-term impacts. As a consequence, the chain starts with the need or the problem, which is adverse weather (drought) and limited access to credit. This creates the need of a risk transfer mechanism. We use a satellite-derived drought indicator combined with household crop yield information to design the RCC. Because the embedded insurance component of RCC substitutes for collateral, it can attract risk-rationed farmers into the credit market. In RCC the indemnity from the insurance reduces farmers' debt obligation, thereby reducing the probability of default on loans by farmers, improving risk bearing ability and trust, increasing the uptake of RCC. Since RCC does not require farmers to pay the premium upfront rather farmers receive credit upfront and repayment depends on the production risk they face RCC can contribute to high and sustained uptake by farmers. Subsequently, RCC increases investment in smallholder maize and wheat production, resulting in a positive effect on household income and reduces the need for emergency response in case of a climatic shock. In the long-run the proposed pathway has the potential to reduce chronic vulnerability and increase disaster resilience for smallholder farmers in Kenya and is naturally scalable to many other economic and ecological conditions that impact agriculture.

Figure 10: Project theory of change diagram

	Impact Pathway				
Needs	INPUT	OUTPUT	OUTCOME	IMPACT	Long-term Development
Farmers in Kenya face drought risk and are credit constrained; Farmers need innovative financing to create social safety nets	Satellite-derived combined drought index Information about vulnerabilities/ coping capacities on household level	Risk Contingent Credit designed and implemented in collaboration with private sector Drought warning accessible to farmers, decision makers, aid organizations	Increased uptake Increased investment in smallholder maize and wheat production at lower production risk	Increased household income and welfare due to existence of sustainable social safety net Increased coping capacities with respect to climatic shocks	Increased resilience and sustainable agriculture for smallholder farmers Decreased need for external assistance (emergency response)

Assumptions

1. Conducive regulatory environment for RCC implementation
2. Sufficient uptake of RCC by farmers
3. Good working relationship with partners and stakeholders
4. Government amenable to policy and institutional change

4. Monitoring plan

We set up a project monitoring and evaluation (M&E) system to support effective project management, provide data for timely reporting, generate and validate the evidence, and help all stakeholders to learn about project successes and failures. A robust M&E system that provides learning opportunities on what has worked and what has not will in turn inform the project implementation, as well as catalyze adjustments to ongoing activities that might enhance efficiency and effectiveness. The project is committed to achieving a number of specific goals in terms of its deliverables and approach:

- International standards compliance**:** The M&E activities will conform to the overarching M&E standards, best practices, and core indicators established for this type of initiative.
- Open-access platform**:** The M&E activities will deliver and maintain an open-access, transparent M&E data management and analysis platform to serve the needs of researchers and other stakeholders. Open data access is now mandated by both US Government regulations and the CGIAR Consortium, of which IFPRI is one of the network institutions.
- Multi-scale reporting**:** To meet different stakeholder needs, and to provide the capability to support multi-scale monitoring and evaluation, the M&E platform will be designed to report at several scales and levels of aggregation.

Our M&E Plan consists of two separate but interconnected components:

1. A data information system that will use the mobile technology and network. The sharing of indexes and RCC contract information will occur from the data hub,
2. Periodic traditional household surveys, conducted at two points in time as a minimum. They would allow a carefully solid, quantitative impact evaluation using a difference-in-difference ((before-after)-(treated-control)) approach in the context of randomized controlled trial.

The M&E plan will be revised on an annual basis, to take account of the experience of the project and its implementation on the ground to enhance flexibility and adaptation to ever-changing circumstances.

The overall monitoring plan is based on collecting output and outcome indicators across multi-arm randomized controlled trial.

Key outcome indicators Take-up rates, credit rationing status, agricultural investment, productivity, household consumption, vulnerability to shocks, and subjective welfare

Data collection Baseline and follow up household survey data collection for outcome indicators, uptake and loan repayment data monitored by Equity Bank

Input data 5km dekadal (10-daily) CHIRPS rainfall (satellite validated with station data) data from 1981 to present to construct weather index

5. Evaluation questions and primary outcomes

We have the following five impact evaluation questions:

1. Does the insurance feature of RCC encourages risk-rationed farmers to uptake loans?
2. Does uptake of RCC differs among farmers with different characteristics (such as risk preference)?
3. How does uptake of RCC affect farmers' productive behavior and welfare?
4. How does the effects of RCC uptake differ from the effects of uptake of traditional loans?
5. Does the effect of RCC uptake differs among farmers with different characteristics?

In the formative evaluation stage we mainly focus the following: 1) identify the credit rationing status of the sample households, 2) how credit constraints impact the agricultural productivity, and 3) does RCC encourage risk-rationed farmers to uptake loans. Detailed impact evaluation analysis will be done after follow up survey data collection.

The methods for formative evaluation of the above mentioned questions of interest include: a) Direct elicitation using a multiple bounding discrete choice framework of farmers' credit rationing status; b) Elicitation of demand for RCC by the farmers; c) Behavioral experiments within the randomized controlled environment. So far we have found that the average cost of credit constraint for the sample farmers in our study area is about 21% loss in crop revenue. In terms of loan application, we found significantly more loan application for RCC loan compared to tradition loan.

6. Evaluation design, data and methods

To investigate the research questions above, we employed a randomized control trial and behavior experiments. We use mixed methods to identify the potential outcome variables and to understand the pathways through which the outcomes were realized. Firstly, we undertake qualitative investigations including focus group discussions and informal interviews with households in selected sites. Through these qualitative approaches we aim to (i) understand what kind of impacts to expect; (ii) inform survey instrument to be applied; (iii) develop the hypotheses that could be modelled and tested against the survey data; (iv) understand the pathways of possible impacts and the time path of these impacts; and (v) provide complementary evidence to support the results of the quantitative analysis. Then, we use quantitative methods to measure the magnitudes of impacts on these outcomes and to verify the underlying mechanism.

Following are the activities and how they are implemented for formative evaluation: (1) We use the Tegemeo Agricultural Policy Research and Analysis (TAPRA) data from 2000 to 2010 that covers our target County, Machakos to carry out power and sample size calculation. (2) We identify a pool of farmers who are interested in receiving a loan for agricultural investment purpose and to whom the bank would be willing to offer a loan. These farmers form our sampling framework. We randomly select households from the identified pool. (3) We conduct the baseline survey. In the survey, we collect household demographics, welfare indicators, agricultural investment and farming practices and other outcome variables specified in our qualitative analysis. We also conduct behavioral experiments to elicit farmers' risk preference and credit rationing status. (4) We employ household level multi-arm randomized controlled study with village/community level stratification. We plan to compare the following three research groups: treatment 1 (traditional credit), treatment 2 (RCC) and control (no credit). Some additional households are part of a sub-experiment of demand estimation where households receive random subsidy (25%, 50%, and 75%) on risk premium. This sub-experiment will help us elicit demand elasticities for RCC that can provide important policy perspectives. (5) We plan to conduct a follow up survey. We will collect household welfare indicators, farming practice and other outcome variables. We will also collect farmers' feedback on RCC in order to improve our product and delivery channels. (6) We will then analyze the baseline and follow up data to answer our research questions.

The proposed sample design would allow us at 80% power to detect impacts of RCC on agricultural investment and maize yield (as predicted by the theory of change) that are no smaller than 15% of the initial levels of these variables. We believe that the minimum detectable effect of the program will be no smaller than 15%. We assume that the significance of the treatment effect will be determined using t-test. Figure 1 and 2 illustrate how treatment sample size requirement changes with different compliance (take-up) rates for investment and maize yield, respectively given 80% power of the test. With an expectation of uptake of about 70-75%, the graphs suggest about 350 treatment group households for our experimental design.

Figure 11: Sample design using Tegemeo TAPRA data on agricultural investment for Machakos

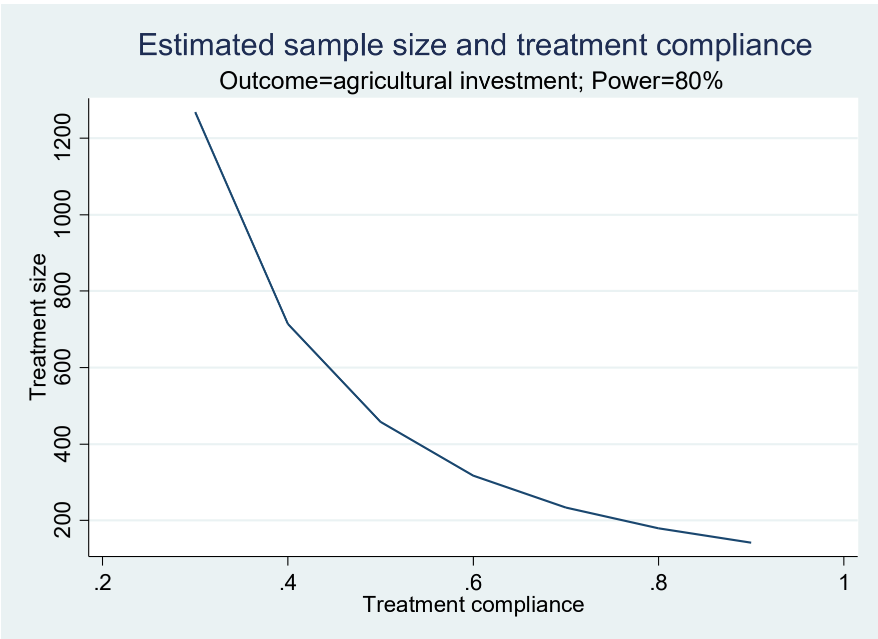
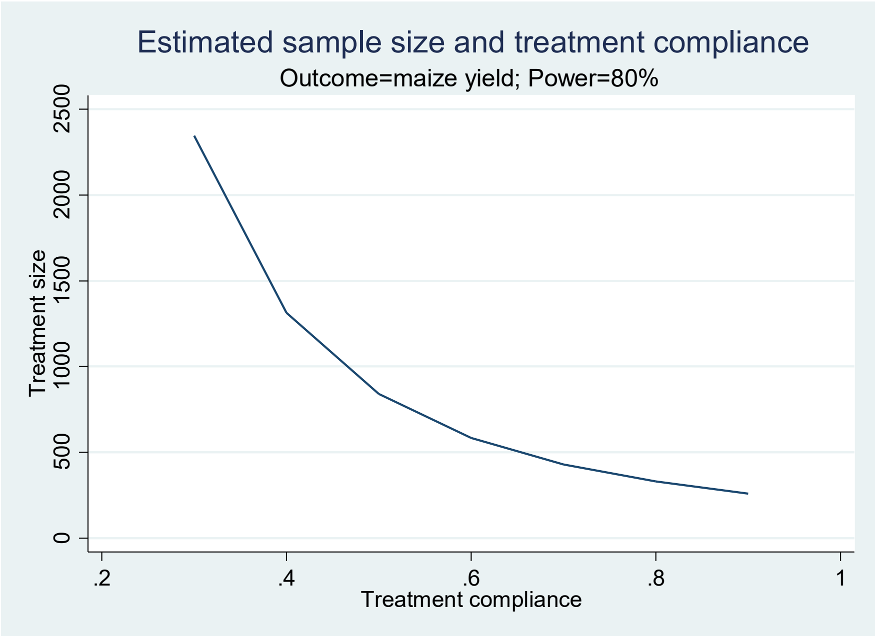
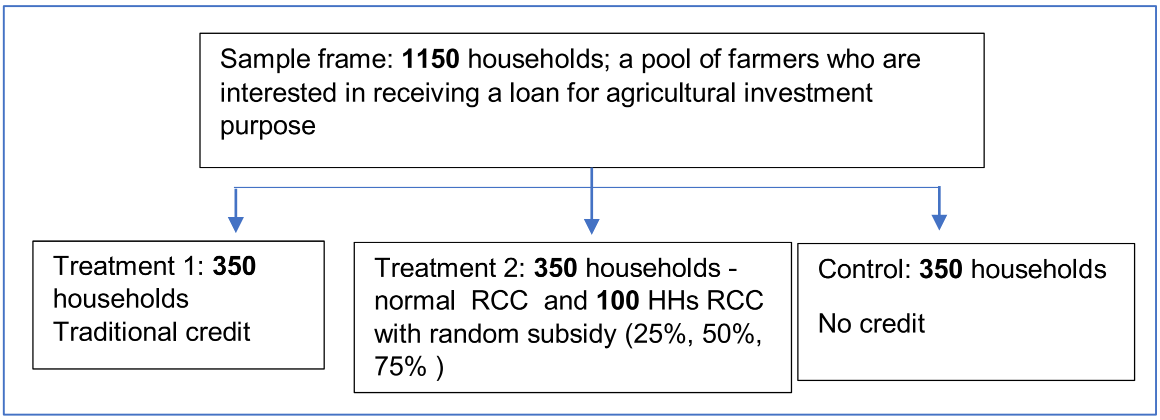


Figure 12: Sample design using Tegemeo TAPRA data on maize yield for Machakos



Note: As can be seen, with a 75% net compliance rate and adequate statistical power (80%) our optimal treatment size will be about 350. Note that the average agricultural investment (without seed) for Machakos county in TAPRA data is 3159 Ksh, while the average main season (long) maize yield is 477.9 Kg/Acre.

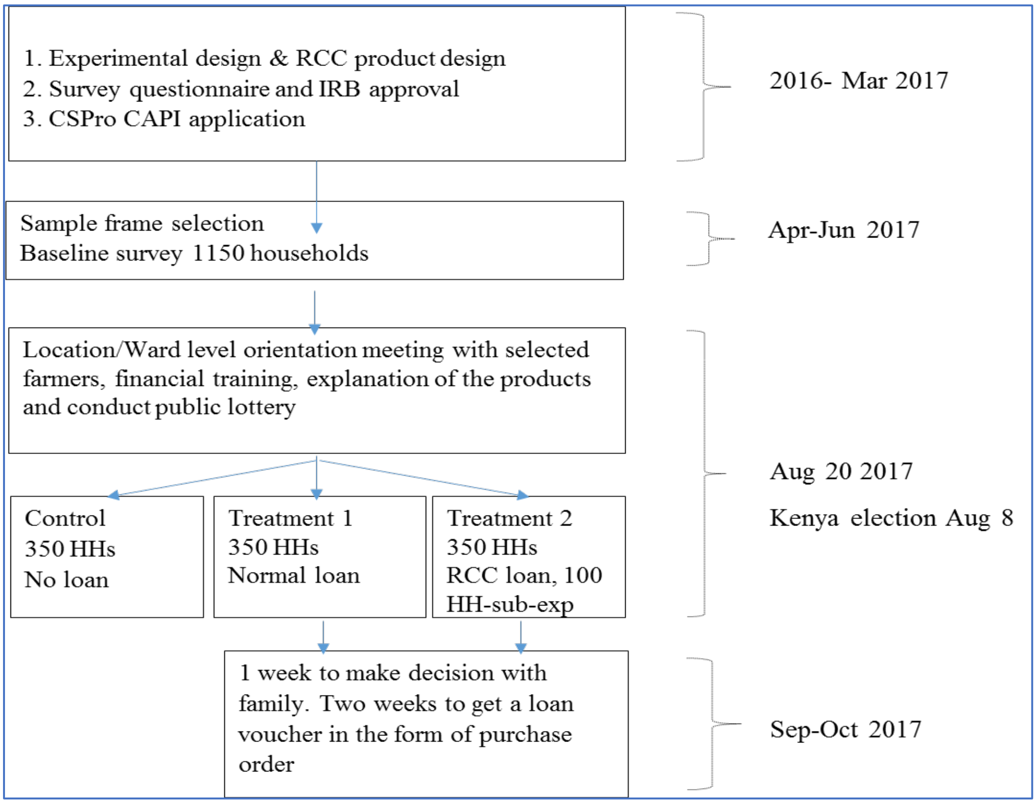
We prefer individual randomization over cluster design because a) RCC is not likely to create competition in the area and hence we are not interested in measuring spillover, b) individual randomization provides better statistical power compared to cluster design because in our settings we could get only a small number of clusters, and c) treatment will be administered at individual household level. Randomization will be conducted publicly so that no resentment is generated against our implementer, Equity Bank. Public lottery will make sure that participants know the winners and losers. The flow of households in the multi-arm randomized control trial is provided below.



7. Study timeline

Following are the activities and how they were implemented for formative evaluation: (1) We carried out power and sample size calculation using the Tegemeo Agricultural Policy Research and Analysis (TAPRA) data from 2000 to 2010 that covers our target County, Machakos in Eastern Kenya. At the same time we analysed CHIRPS rainfall (satellite validated with station data) data from 1981 to present to construct weather index and actuarially fair pricing of RCC product. (2) We identified a pool of farmers who are interested in receiving a loan for agricultural investment purpose and to whom the bank would be willing to offer a loan. These farmers form our sampling framework. We have randomly selected households from the identified pool. (3) We conducted the baseline household survey in May 2017. We employed Agri-Food Economic Africa to conduct CAPI based household survey. In the survey, we collected household demographics, welfare indicators, farming practices and other outcome variables specified in our qualitative analysis. We also conducted behavioral experiments to elicit farmers' risk preference and credit rationing status. (4) We conducted location-level financial training and public lottery to randomize the sample into three groups: traditional credit (treatment 1; 350 households), RCC (treatment 2; 350 households) or control (no credit; 368 households), remaining 102 households were part of a sub-experiment of demand estimation where 34 households received 25% subsidy, another 34 households received 50% subsidy, and rest 34 household received 75% subsidy. After establishing the treatment and control groups farmers were given one weeks to discuss in the household. After one week the farmers submitted their application for loan to the local Equity Bank branch. (5) In the next phase of this project, we will conduct two follow up surveys. We will collect household welfare indicators, farming practice and other outcome variables. We will also collect farmers' feedback on RCC in order to improve our product and delivery channels. (6) In the next phase of this project, we will analyze the baseline and follow up data to conduct full impact evaluation of the project. Following is the summary of the study timeline.

Figure 13: Study timeline



8. Analysis and findings from the evaluation

In the formative evaluation stage we mainly identify the credit rationing status of the sample households, how that impacts the agricultural productivity, and does RCC encourage risk-rationed farmers to uptake loans. Detailed impact evaluation analysis will be done after follow up survey data collection.

8.1 Identifying credit rationing status

Identifying credit constraint status of individual household is challenging and requires series of questions on experience and perception of credit. We directly elicit household's credit constraint status for borrowers and non-borrowers using survey-based technique akin to contingent valuation. Household's credit rationing typology can be identified and analysed using farmer's self-reported data. Figure 2 depicts the structure of our direct elicitation approach to identifying credit constraint status for a household. We can divide households in two groups; groups that do not have to apply for a loan instead they are offered loans by their local banks, cooperatives and grain buyers, and groups that must have to formally request for a loan. In the first group, there are no households that are quantity rationed because they are offered a loan. We ask them how much loan they were offered and how much they actually used. Risk rationed households are identified by those who responded that they used less amount than what they were offered, because they are afraid of collateral.

To the households in the second group we ask if they applied for a loan in last two years. If the answer is yes and they received no offer from local banks/ cooperatives or are offered an amount less than requested than those households are quantity rationed. Price rationed households either accepted the offered loan or did not accept loan because of risk associate with loan contract. Risk rationed households did not accept the offered loan because they were afraid of losing collateral. It is important to note that borrower might know lender's supply rule, and might have requested for the amount he qualified for. The most challenging is to classify the households that did not apply for credit. They might not have applied because; they had personal saving and do not need loan (price rationed), they knew they would be rejected (quantity rationed), they were afraid of losing collateral (risk rationed), or they were discouraged by high transaction cost. After proper identification of different types of credit rationing groups according to this direct elicitation method, we do comparative analysis of cost of credit constraints with and without risk rationing.

Figure 14: Structure of credit constraint status module (adapted and modified from Chiu et al. 2014, Boucher et al. 2009)

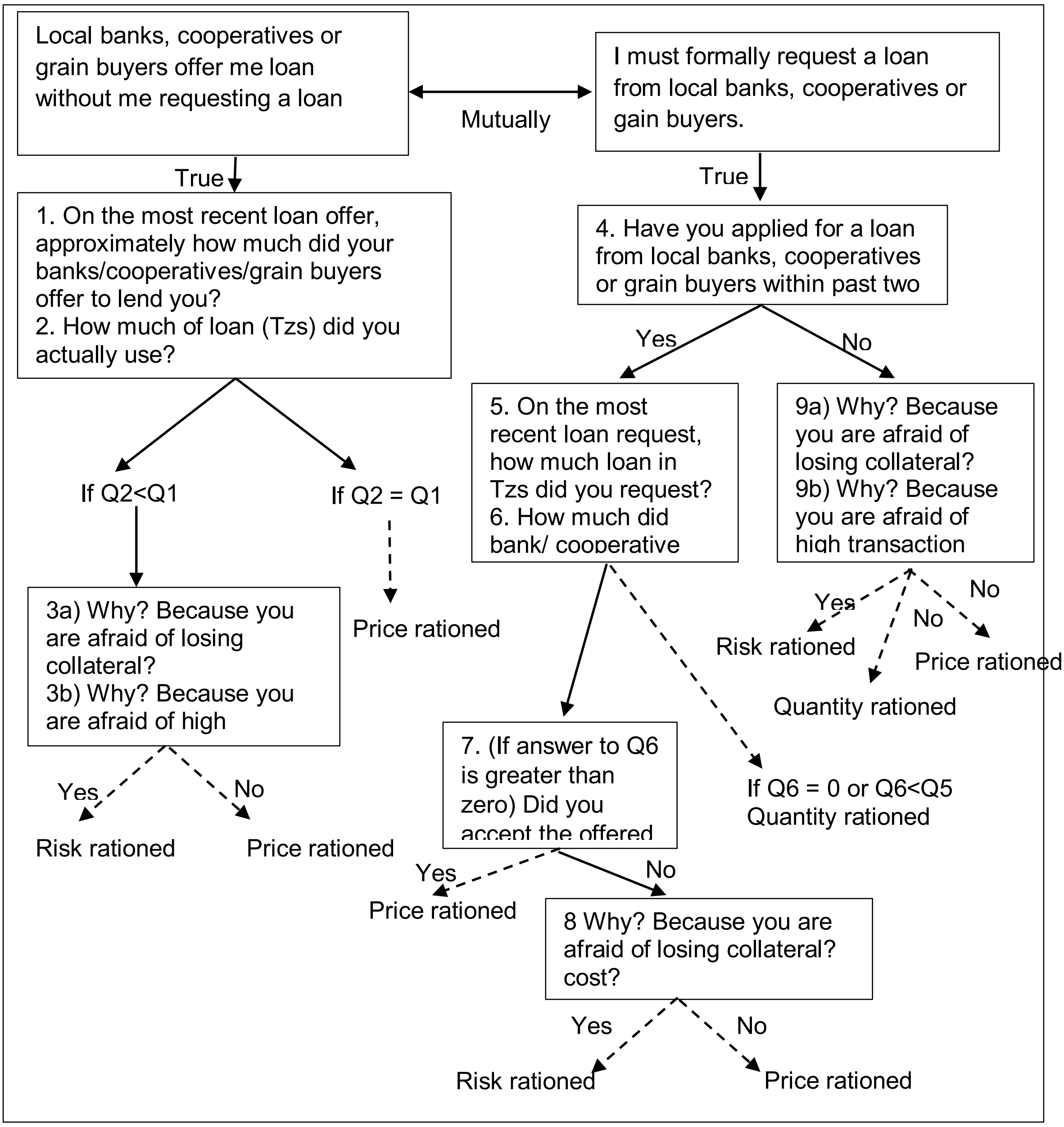


Table 2 shows that a modest 10 percent of households are quantity rationed whereas 42% households are risk rationed. Figure 3-4 shows that quantity and risk rationed households have significantly lower maize yield and crop revenue per acre compared to unconstrained households.

Table 2: Crop revenue and maize yield per acre for different credit rationing groups

Rationing mechanism	Frequency	Percent	Crop revenue in KES/acre	Maize yield in kg/acre
Unconstrained	560	48.07	10,973.11	270.36
Quantity rationed	122	10.47	8,308.03	200.96
Risk rationed	483	41.46	8,495.49	229.64

Figure 15: Avg per acre revenue by credit rationing status

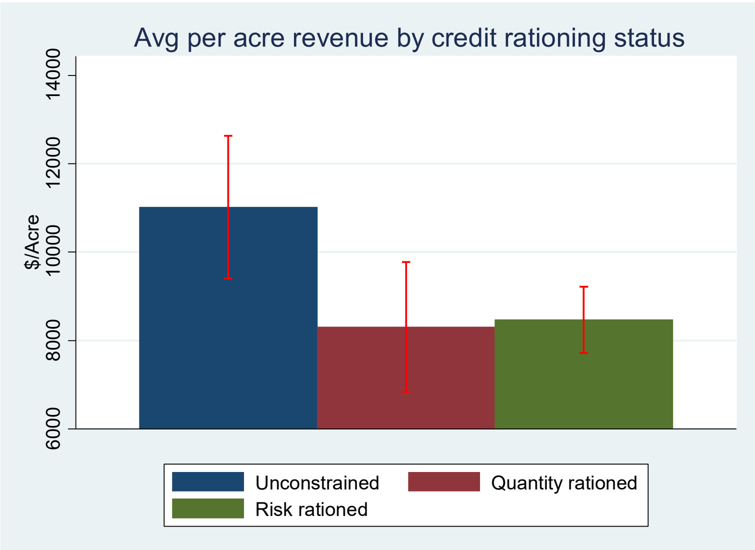


Figure 16: Avg per acre maize yield by credit rationing status

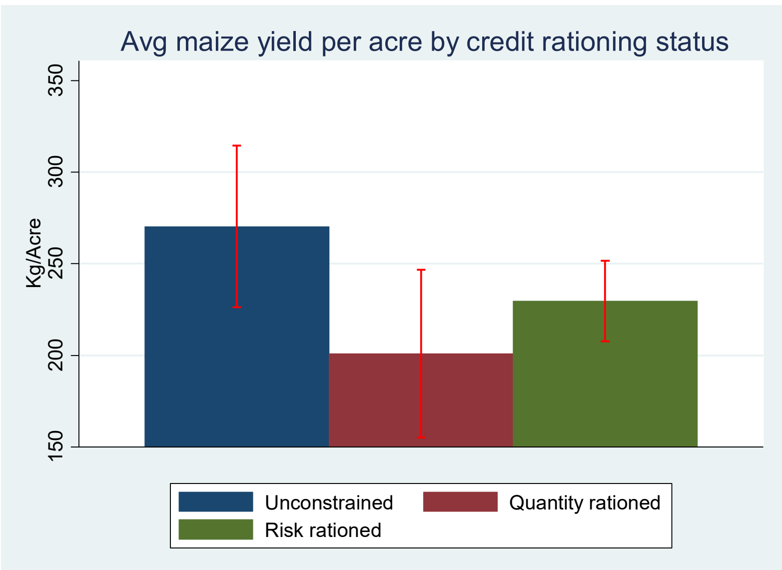


Table 3: Explanatory variables by credit constraint status

Credit rationing group	Unconstrained	Quantity rationed	Risk rationed	Total
Yield of maize(kg/acre)	270.36*	200.96	229.64	246.19
Crop revenue (KES/acre)	11017.97***	8308.03	8469.94**	9677.33
Household size	5.44	5.75*	5.34	5.43
Female headed household	0.18***	0.16*	0.27***	0.21
Age of the head	55.84	56.1	57.34*	56.49
Max years of education in the household	11.52***	11.38	10.50***	11.08
No. of working age labor	3.37**	3.28	3.11**	3.25
Avg no. of sick days in last year	10.09*	17.71**	12.3	11.82
Total land size (Acre)	4.80***	3.95	3.10***	4.01
Distance from the hh to the closest plot	1.06	1.05	1.05	1.06
Soil type 1=good 0=poor	0.76	0.79	0.76	0.76
Soil color 1=good 0=poor	0.87	0.93**	0.87	0.88
Average travel time to seed supplier(minute&oneway)	30.33	28.96	30.92	30.43
Tropical Livestock Units: total	8.56	1.61	13.44	9.84
Total wealth index	0.11***	-0.08	-0.11***	0
CRRA risk aversion coefficient	3.3	3.3	3.44	3.36

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

Source: Project baseline household survey data

Table 3 presents the summary of the means and significance tests of equality of means among three credit rationing groups. Compared to quantity rationed and risk rationed households unconstrained group of households exhibit higher land size, higher number of working age laborer, and higher wealth index.

8.2 Estimation results

To estimate the heterogeneous impact of credit rationing we employ a generalized version of Heckman’s selection model to account for farmers’ self-selection based on unobserved heterogeneity. Unobserved heterogeneity occurs when the unobservable components affecting the expected outcome for a given household are different when such a household is treated or untreated. Since the selection model under joint normality assumption is fully parametric, the estimation routine employ a maximum likelihood estimation, thus yielding consistent and efficient estimates. We show the results of treatment effect estimates for crop revenue per acre in Table 4.

Table 4: Result of selection model under alternative definition of credit constraint

VARIABLES	OLS	Treatment heterogeneity	
		Log revenue ($/acre)	Credit constrained HH
Credit constrained HH	-0.112*	-0.225	
	(0.058)	(1.143)	
HH size	-0.038**	-0.034	0.052**
	(0.019)	(0.029)	(0.026)
Female headed HH	-0.167**	-0.166*	0.151*
	(0.070)	(0.099)	(0.097)
Age of HH head	0.025	0.031	0.022
	(0.017)	(0.027)	(0.023)
Sq of age of HH head	-0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Distance to closest plot	-0.115	-0.169	-0.147
	(0.101)	(0.147)	(0.141)
soiltype	-0.081	-0.083	-0.005
	(0.069)	(0.069)	(0.094)
soilcolor	-0.117	-0.110	0.122
	(0.090)	(0.102)	(0.124)
No. working age labor	0.013	0.026	-0.115***
	(0.027)	(0.063)	(0.038)
No. sick days last year	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)
Travel time to seed supplier	-0.001	0.000	0.002
	(0.001)	(0.002)	(0.002)
Wealth index	0.022	0.015	-0.191***
	(0.029)	(0.067)	(0.054)
CRRA	-0.013	-0.013	-0.003
	(0.010)	(0.011)	(0.014)
Constant	8.863***	8.694***	-0.672
	(0.499)	(0.791)	(0.689)
Observations	1,038	1,038	
R-squared	0.033	0.037	

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Having assumed heterogeneous response to treatment allows us to calculate the other important parameters of interest, ATET and ATENT that shows the cross unit distribution for credit constraint and credit unconstraint households, respectively. Table 5 provides the coefficients and bootstrapped standard errors for ATET and ATENT. The estimated ATET coefficient being -0.128 implies that the average cost of constraint for farmers who are currently credit constrained is 13% loss in productivity. The average cost of constraint is even higher (28% loss in productivity) for a farmer who is currently unconstrained. Since the cost of constraint is higher for the unconstrained set of farmers they self-select into being unconstrained.

Table 5: Coefficients and Bootstrap standard errors for ATET(x) and ATENT(x)

	Observed Coef.	Bootstrap Std. Err.	z	P>z	Normal-based [95% Conf. Interval]	
atet	-0.1286	2.706528	-0.05	0.962	-5.433298	5.176097
atent	-0.32661	2.731495	-0.12	0.905	-5.680244	5.027019

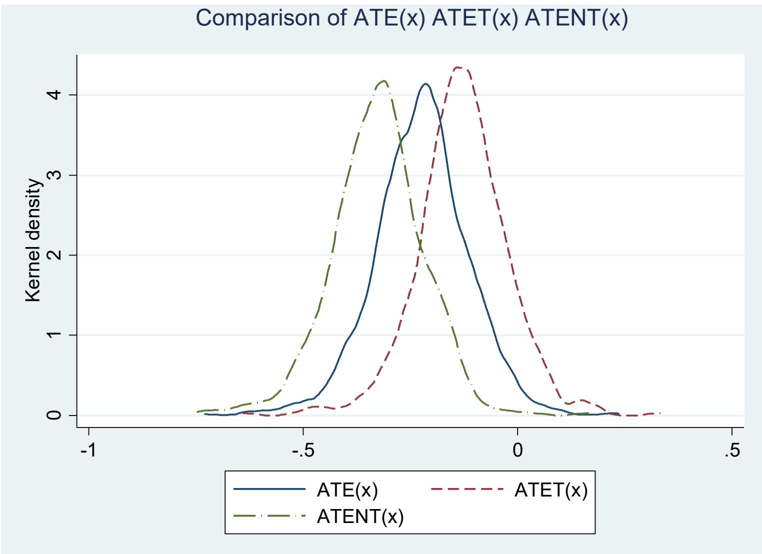
Table 6: Decomposing Bias in Estimation of Credit Constraint with Risk Rationing

Revenue	Coefficient	Percentage difference
OLS	-0.112	-11%
ATE	-0.225	-21%
ATET	-0.128	-13%
ATENT	-0.326	-28%
Sorting bias	(ATET-ATE)	8%
Selection bias	(OLS-ATET)	2%

Table 6 presents a comparison among various treatment parameters. Since the outcome variables are in log terms they have been converted into percentage terms in the next column[1].

Figure 5 plots the average treatment effect distributions. The plots exhibit similar pattern, with a strong demarcation between ATET and ATENT. ATENT(x) looks concentrated on more negative values than ATET(x). What does this mean? This means different counterfactual conditions: on average, if an unconstraint household become credit constraint, then the productivity of that household would decrease more than the increase in productivity of a credit constraint household becoming unconstraint.

Figure 17: Distribution of ATE(x), ATET(x), and ATENT(x)



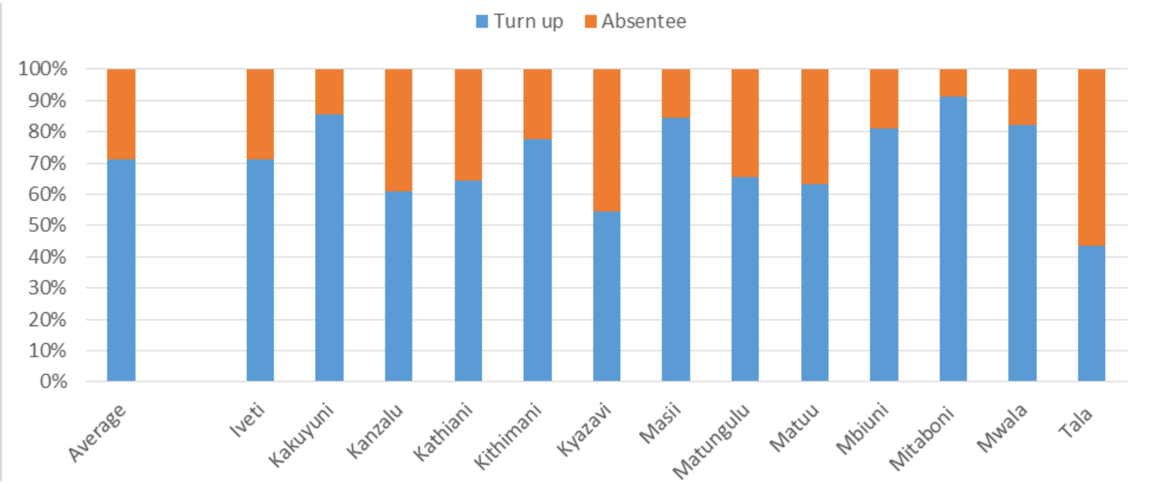
[1] Outcome variables are calculated in log terms: ln $Y_1 - lnY_0 = -0.112$ or $Y_1 \approx 89\%\, Y_0$ meaning 11% loss in productivity due to credit constraint.

In summary, we find that the average cost of credit constraint for the entire population of farmers in our study area is about 21% loss in crop revenue. If the constraint is removed from a constrained farmer, on average his/her productivity is expected to increase by 13%, and if credit constraint is imposed on an unconstrained farmer, he/she is expected to suffer a very high 28% loss in productivity. We have found that average cost of constraint for the unconstrained set is much higher than that of the constrained set which indicates that the principle of comparative advantage is at work.

8.3 Participation at location-level financial training

The financial trainings for the farmers were conducted from Wednesday September 20, 2017 to Friday September 29, 2017. The graph below shows the average turn up for the trainings as well as turn up within locations. The average was 71% (64 farmers in a location) with highest being Mitaboni with 91% (82 farmers) and the lowest Tala with 43% (39 farmers). The total number that was expected from each location was 90 farmers who were randomly selected to participate in the RCT during the baseline survey which was conducted earlier in the year.

Figure 18: The Turn up rates for the financial knowledge trainings



8.4 Preliminary uptake of loans

After the financial training a public lottery was conducted in each location where all sample farmers were distributed in three groups: traditional credit (treatment 1; 350 households), RCC (treatment 2; 350 households) or control (no credit; 368 households), remaining 102 households were part of a sub-experiment of demand estimation where 34 households received 25% subsidy, another 34 households received 50% subsidy, and rest 34 household received 75% subsidy. After establishing the treatment and control groups farmers were given one weeks to discuss in the household. After one week the farmers submitted their application for loan to the local Equity Bank branch. Table below summarizes the submitted loan applications. As expected we see very high (80%) uptakes of loan in the RCC loan group whereas the uptake of the tradition loan was very low, about 20%. This data supports our hypothesis that RCC encourages risk-rationed farmers to take-up loans. We plan to conduct further analysis to determine the determinants of loan uptake as soon as we receive full loan amounts from the bank branches. The loans are being disbursed by the Equity bank branches at the moment.

Table 7: Loan uptake rates

RCT groups	No. of farmers	Loan application submitted
Control	368	
Traditional loan	350	20%
RCC loan	350	80%
RCC with 25% subsidy	34	90%
RCC with 50% subsidy	34	93%
RCC with 75% subsidy	34	100%
Total	1170	

9. Implications of study findings

The RCC research, implementation and impact assessment agenda has to date been quite comprehensive. The RCC project has been problem-driven from the outset with needs and challenges identified through extensive household survey work and interaction with the target community. Our RCC product has many innovative features. It appears to be the first to develop scientific bundling of rainfall based index insurance and agricultural term loan through actuarially fair pricing. Because the insurance component of RCC substitutes for collateral, it is more financially inclusive than conventional credit products. In RCC the indemnity from the insurance is applied to the underlying debt obligation or debt service, thereby reducing the probability of default on loans by producers, improving their risk bearing abilities, and bridging trust in the lender-borrower relationship. By design, RCC mitigates business risks faced by the farmer (failure of long and/or short rains) and financial (credit) risks faced by the lender. This form of risk balancing can not only encourage supply (as it is already doing with our partner, Equity Bank) but also encourages credit use targeted towards more economically efficient input use at the intensive margin. With insurance at least partly offsetting risk to collateral, RCC can encourage high uptake of credit, particularly by risk-rationed farmers. Our finding of very high (80%) volume of loan application for RCC loan provides a signal that by minimizing credit risk RCC is able to attract risk-rationed farmers into formal credit market. This potential high uptake will help the project conduct high quality full and long term impact study in phase 2 of this window.

Using direct elicitation of credit constraints through a specialized survey along with our baseline survey we identify and estimate the average cost of credit constraint on agricultural productivity for constrained, unconstrained, and the entire sample population. We directly elicit household's credit constraint status for borrowers and non-borrowers using survey-based technique akin to contingent valuation. We have found a modest 10% of households are quantity rationed whereas 42% households are risk rationed. We employ a generalized version of Heckman's selection model to account for farmers' self-selection based on unobserved heterogeneity and find that the average cost of credit constraint for the entire population of farmers in our study area is about 21% loss in crop revenue. If the constraint is removed from a constrained farmer, on average his/her productivity is expected to increase by 13%, and if credit constraint is imposed on an unconstrained farmer, he/she is expected to suffer a very high 28% loss in productivity. We have found that average cost of constraint for the unconstrained set is much higher than that of the constrained set which indicates that the principle of comparative advantage is at work. By estimating heterogeneous response to credit constraint this study not only estimates the average cost of credit constraint for the entire population but also estimates the full distribution of cost of constraint including other important parameters of policy interest such as the average cost of constraint for the constrained and the unconstrained set of households.

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