Uptake of Insurance-Embedded Credit in Presence of Credit Rationing: Evidence from a Randomized Controlled Trial in Kenya

Michael K. Ndegwa[*1] Apurba Shee[1] Calum G. Turvey[2] Liangzhi You[3]

[1]Natural Resources Institute (NRI), University of Greenwich, Medway Campus, Central Avenue Chatham Maritime, Kent. ME4 4TB, UK

[2]Charles H. Dyson School of Applied Economics and Management, Cornell University

450A Warren Hall Ithaca, New York 14853-7801

[3]International Food Policy Research Institute (IFPRI) 2033 K-Street, NW, Washington, DC 20006, USA

[*]Correspondence: M.K.Ndegwa@greenwich.ac.uk, mikekndegwa@gmail.com

Abstract

Purpose – Drought related climate risk and access to credit are among the major risks to agricultural productivity for smallholder farmers in Kenya. Farmers are usually credit constrained either due to involuntary quantity rationing or voluntary risk rationing. By exploiting randomized distribution of weather risk-contingent credit (RCC) and traditional credit, we estimate the causal effect of bundling weather index insurance to credit on uptake of agricultural credits among rural smallholders in Eastern Kenya. Further, we assess farmers' credit rationing, its determinants and effects on credit uptake.

Design/methodology/approach – The study design was a Randomized Controlled Trial (RCT) conducted in Machakos County, Kenya. 1170 sample households were randomly assigned to one of three research groups: 351 farmers assigned to receive traditional credit; 351 farmers assigned to receive RCC; 117 farmers assigned to receive RCC with subsidies on insurance premium; and 351 farmers assigned to receive no credit. This paper is based on baseline household survey data and the first phase of loan implementation data.

Findings – We find that 48% of the households were price-rationed, 41% were risk-rationed and 11% were quantity-rationed. The average credit uptake rate was 33% with the uptake of bundled credit being significantly higher than that of traditional credit. Risk rationing seems to influence the credit uptake negatively whereas premium subsidies do not have any significant association with credit uptake. Among the socio-economic variables, training attendance, crop production being the main household head occupation, expenditure on food, maize labour requirement, hired labour, livestock revenue and access to credit are found to influence the credit uptake positively whereas the expenditure on non-food items is negatively related with credit uptake.

Research limitations/ implications – Our findings provide important insights on the factors of credit demand. Empirical results suggest that risk rationing is pervasive and discourages farmers to take up credit. Our results also imply that credit demand is inelastic in our study sample although relatively small sample size for RCC premium subsidy groups may be a limiting factor of our estimation.

Originality/value – By implementing a multi-arm RCT we estimate the factors affecting the uptake of agricultural credits along with eliciting credit rationing among rural smallholders in Eastern Kenya.

Keywords: Risk-contingent credit, Index insurance, Credit rationing, Credit uptake, Bundled insurance
Paper type: Research paper

This research is part of Michael Ndegwa's doctoral dissertation at the Natural Resources Institute of University of Greenwich supported by the Vice Chancellor Scholarship. This research was supported partly by the Global Resilience Partnership (GRP) through the Round 1 Global Resilience Challenge, supported by USAID in the context of a project titled "Satellite Technologies, Innovative and Smart Financing for Food Security (SATISFy)" and partly by Agricultural Insurance Thematic Window of the International Initiative for Impact Evaluation (3ie). The work was also undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by IFPRI. We appreciate generous hospitality provided by our project partner Equity Bank Kenya Ltd. The opinions expressed in this paper do not necessarily reflect the views of our donor or partners. Any errors that may remain are the authors' responsibility.

Uptake of Insurance-Embedded Credit in Presence of Credit Rationing: Evidence from a Randomized Controlled Trial in Kenya

1.0 Introduction

Rural households from low income countries have listed unfavourable weather conditions as one of the most important risks affecting productivity and household resilience (Cole., 2012). For instance, analysis of household risks from Malawi by Giné & Yang (2009), from Ethiopia by Dercon and Christiaensen (2011) and from India by Cole et al. (2013) confirm that rainfall variability and shocks are the largest source of risk to agricultural productivity and consumption. Moreover, weather risks and climate shocks are critically important constraints to wealth accumulation, particularly for those in rural areas who are either engaged in agricultural activities or have their livelihoods tied to the well-being of the farming sector (Barrett et al., 2007). Consequently, many farmers from developing countries have low capacity to adapt to weather related risks. Covariate impacts can also have a rippling effect throughout the rural and agricultural economies affecting farm workers, input suppliers, entrepreneurs and workers in agribusiness, and providers of non-tradable goods and services in the rural non-farm economy (Carter et al. 2014). Governments and development agencies are not spared as they face sudden demands for relief, reconstruction, and recovery (Carter et al., 2014; Chantarat et al., 2007; Chantarat et al., 2008; Cummins & Mahul, 2009).

To help farmers cope with the impacts of weather shocks, several interventions have been tried. Most of them have been developed under the Climate Smart Agriculture (CSA) umbrella with adaptive capacity, sustainable intensification and Green House Gases (GHGs) mitigation as the main goals (Branca 2012). They range from conservation agriculture (CA), to stress tolerant crop varieties, pests and diseases management methods, promotion of adaptable alternative crops and animals, capacity building and gender mainstreaming as well as innovative ways of timely sharing the right information with farmers, mostly through mobile phones. Such interventions have been developed and promoted mostly by governments and the donor community and are mostly targeted towards promoting new and efficient technologies. However, the impacts of weather shocks on agriculture are huge and covariate in nature, and at times catastrophic. As such, the public sector cannot solve them on their own. There is need for market-based interventions to (1) help the farmers afford and adopt such technologies and/or practices, and (2) protect them against weather and climate risks. To provide farmers with risk protection, different insurance contracts have been tried where weather index insurance has been developed to particularly provide hedging against weather shocks. Carter et al. (2014) define Index-Based Insurance (IBI) as a major institutional innovation that could revolutionize access to insurance for millions of smallholder farmers. Similar agricultural insurance products have been offered to farmers for quite some time now especially in the developed and industrialized countries although under high levels of public subsidies (Turvey 2001; Glauber 2004; Carter et al. 2014) (Smith and Watts, 2009).. For the last two decades, index insurance products have been introduced in several low-income countries at individual (micro) and/or institutional (meso) levels but mostly as pilot and/or experimental projects (Carter et al., 2014).

The impact of weather and climate risks on smallholder farming is further compounded by the fact that farmers lack capital and have limited to no access to credit, especially from formal credit institutions. This undermines their capacity to afford/adopt high yielding technologies. Access to credit has, however, been found to be positively correlated to productivity and resilience among the rural farming households, who are mostly small scale farmers (Muhamma & Jan, 2011). Lack of credit constrains optimal use of inputs and limits marketing opportunities which eventually lead to disinvestment and poverty traps (Barrett et al., 2007; Chantarat et al., 2017; Shee & Turvey, 2012; Shee et al., 2015).

In theory, credit is an important resource that allows farmers to expand their operations or adopt new technologies to achieve higher productivity and profitability (Dzadze at al. 2012). In practice, the associated financial and liquidity risks that come with credit use constrains its adoption. Risks can not only impact supply-side credit rationing, but also demand side risk-rationing (Boucher et al., 2008; Verteramo-Chiu et al., 2014). In principal, banks use restrictive lending policies to avoid loss on investments. Because of risk of default, they are hesitant to not only lend but also increase interest rates on those they deem as risky borrowers. They either give less credit than demanded or reject them altogether (Chodechai, 2004; Stiglitz & Weiss, 1981). This leads to credit/quantity rationing, a non-temporary disequilibrium condition with excess demand for credit than the banks are willing to supply. On the other hand, the banks may require relatively high collateral to cover the risks of the credit to be advanced. This may in return expose farmers to unacceptable risk of collateral loss and hence they voluntarily excuse themselves from the credit markets and hence they are risk rationed (Boucher et al., 2008; Boucher et al., 2009).

Part of the problem can be resolved with agricultural insurance. In theory, index-based insurance provides farmers with risk cover and removes the fear of investing in new technologies while credit, on the other hand, would enable them to access/afford those technologies. On its own, insurance may be ineffective since most of the time farmers are liquidity constrained to even afford the premiums that are usually required to be paid upfront

(Chantarat et al., 2017) and (Smith and Watts, 2009). Combining insurance with credit is hence crucial to achieve the dual advantage of risk cover and adoption of technologies. Carter et al. (2011) showed that uptake of improved technology will be low if efforts to link credit and insurance are not made. However, financing in agriculture in low income countries is underdeveloped as evidenced by low to zero portfolios of agricultural loans by financial institutions. For instance, in Kenya, even after the government made efforts to focus on agriculture to eradicate poverty and increase food security, Kenyan banks still hold less than 5% of agricultural loans in their portfolios (Maloba & Alhassan, 2019).

To borrowers, business risks increase financial risks, and to lenders financial risks increase business risks. This natural incompatibility is difficult to resolve but bundling insurance with credit can bridge the credit access gap between the financial institutions and rural smallholder farmers. Bundled, or risk-contingent credit are designed to shift risk from both the farmer and the financial institution to the insurance markets[1].

Substantial effort has been made towards integrating insurance and credit for smallholder farmers albeit at theoretical and experimental level. For instance, Giné and Yang (2009) conducted a randomized field evaluation of traditional and rainfall index insured credits in Malawi and found higher uptake of traditional credit than the insured credit. Karlan et al. (2011) attempted to compare traditional credit with a price contingent credit in Ghana to assess if whether risks have any effect on investment. It was however impossible to evaluate this since uptake for both credit types was high and homogenous. They in the end recommended further research but with other risks, such as rainfall variability, with larger sample sizes, training and longer-term commitments to maintain meaningful presence in a market. Carter et al. (2011) theoretically studied the impacts of insurance-linked credit on financial market deepening and small farm productivity and concluded that for index insurance to work, it must be contractually interlinked with credit needed to capitalize the adoption of new improved technologies. Shee and Turvey (2012) developed a risk contingent credit as an alternative to traditional agricultural credit and working with simulated field data from pulse farmers in India, concluded that it provided downside risk protection against commodity price fluctuations.

This paper is part of a wider study dubbed Satellite Technologies, Innovative and Smart Financing for Food Security (SATISFy) implemented by IFPRI, NRI, Equity Bank, APA

[1] Although our approach is at the micro-level, it is consistent with previous studies which recommend moving IBI from considering specific households to various local level risk aggregators (organisations that do business with farmers) may be more appropriate (Barnett & Mahul, 2007; Farrin & Miranda, 2015; Glauber, 2004; Pelka, Musshoff, & Weber, 2014; von Negenborn, Weber, & Musshoff, 2017). They include lenders such as banks, MFIs as well as farmer associations.

Insurance and other partners. It aimed at developing a weather index-insurance linked credit and to evaluate its impacts on promoting resilience and food security for smallholder farmers. Related work has been done with several theoretical prepositions but limited empirical research (Jensen and Barrett, 2017). For instance, Shee & Turvey (2012) proposed a Risk Contingent Credit (RCC) model which implies a credit instrument bundled with index insurance, transferring part or all of the borrower's liability to the lender or insurer if triggered. Giné and Yang (2009) investigated adoption of an operating loan in Malawi where the payoff was determined by rainfall, and Shee and Turvey (2012) proposed downside risk protection for the pulse farmers in India. A recent review by Marr et al. (2016) asserts that only limited empirical research has been conducted on the impact of bundled products such as combination of insurance and credit. They concluded that the extent to which credit suppliers would react to the insured status of farmers is unknown as well as the farmers' preferences when it comes to a mix of financial products. This study aims at making significant contribution in investigating the determinants of uptake of such a bundled financial product. This paper in particular aims to (1) establish the credit rationing and the drivers of rationing among the rural smallholder households, (2) establish the effect of credit rationing on uptake, (3) assess the uptake of both the traditional credit and RCC and (4) measure the treatment (RCC) effect on loan uptake as well as establish other drivers of traditional credit and RCC uptake.

The remainder of this paper is as follows. In section 2, we present the RCT study design, sampling procedures, data collection, and respondents' descriptive statistics. In section 3, we describe the empirical methodology to identify the determinants of uptake of insurance-embedded credit and the determinants of credit rationing. Finally, in section 4, we present and discuss the estimation results, followed by concluding comments.

2.0 Materials and methods

2.1 Structure of randomized control trial

The study was a Randomized Controlled Trial (RCT) conducted in Machakos County, Kenya. This paper is based on baseline household survey data and the first phase of implementation which took place from April 2017 to June 2018. Five sub-counties were selected in consultation with Equity Bank and provincial administration officials. Thirteen locations, which serve as the clusters for this project, were then selected from the five Sub-counties. Sub counties and locations/cluster selection was purposive considering Equity Bank's coverage and capacity to deliver the proposed products. Later, at the onset of the baseline survey, six villages per location were randomly selected. This was done from villages sampling frame comprising of lists of villages per location which were provided by the Chiefs, the local administrators in charge of locations. Thereafter, the sub-chiefs and village elders from the selected villages provided the research team with household sampling frames including the names of all households under their jurisdiction. Fifteen households per village were randomly selected from the sampling frame giving us 90 households per location and 1170 in total. The baseline survey was implemented from May 16 to June 2, 2017. This was conducted by a team of 30 trained enumerators and supervisors using a pretested questionnaire. Data collection was done electronically using a questionnaire programmed into Tablets using CSPro.

The RCT protocol is illustrated in **Figure 1**. Following the baseline survey, selected farmers were invited to training events which involved games and roll-playing to explain RCC, costs and benefits, payment structures and limitations. The training events were conducted at the location/cluster level (90 households) and targeted either the household head or spouse. It was during this training that households were randomly assigned to the experimental groups by drawing a chip from an urn (Figure 2) [2]. Treatment included one group to be offered traditional credit (N=351) and a second that would be offered RCC (N=351). A third group, used as a control, received no credit offer (N=351). To gather some insights into the demand elasticity of RCC, a subset of 117 RCC members were offered subsidies of 25%, 50% and 75% of the effective costs of insurance premiums. The training events and lotteries were conducted between September 19th - 29th 2017.

[2] This was done as public lotteries whereby each participant blindly drew a chip once from the urn and the outcome was announced publicly and entered against his/her name in the households' lists. Those who were not in the meeting were picked for by the chiefs, sub-chiefs, village elders or someone who knew them. There were 27 chips written Control, 27 written Normal credit, 27 written RCC, and 3 chips of each subsidy categories (25%, 50% and 75% subsidy on premium). This adds up to 90 chips which were just enough for the selected households in a location/cluster.

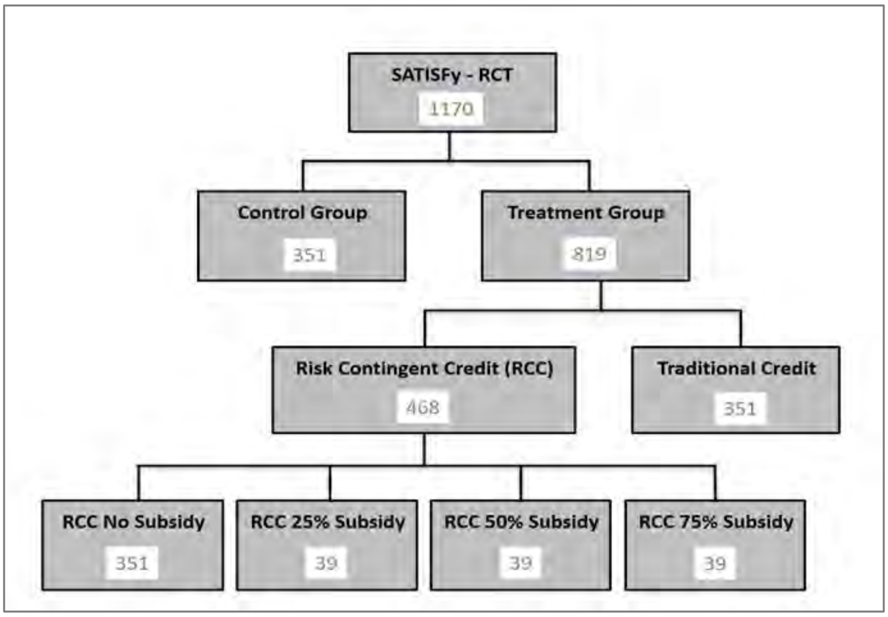

Figure 1: Randomized Control Trial design

Figure 2: The printed chips used during the random assignment lotteries

2.2 Weather index insurance design

The insurance linked to credit in this RCT was based on Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) rainfall measures for the traditional long rain season in Machakos County from October 15th to January 15th. Detailed procedures are reported in Shee et al (2019). In brief, historical dekadal (10-daily) rainfall data from 1981 to present were collected for each of the 11 sub-counties in Machakos County. Cumulative rainfall measures were fit to a PERT distribution, with a cumulative rainfall 'trigger' set at the 20th percentile for each sub-county. Correlated Monte Carlo simulation was used to compute actuarial rates assuming Ksh 300 tick value for every millimetre of rainfall below the trigger. The tick value was determined by the amount required to pay off the loan principal in a worst-case scenario. Although the trigger value and probability distributions differed by sub-county, the actual premiums averaged about 12% across districts. With a 25% loading factor imposed by the insurer, the yield as a percentage of the loan amount was set at 15% for each sub-county, even though each of them had a distinct trigger against which indemnities were to be calculated.

2.3 The lending processes

The RCT provided 'access' to credit for 819 farmers but providing access did not necessarily mean the farmer would accept the offer and use the credit. Since many farmers had no prior interaction with the local lender, Treatment farmers were invited to mandatory meetings where they received further training on the bank's loan processes and, where necessary, opened a bank account. This was a bank-led process with the bank applying conventional rules in due diligence to determine credit worthiness.

To ensure that credit was to be used only in production processes the loan amount was not advanced in cash. Instead, farmers were provided vouchers which they used to collect inputs from local Agrovet supply shops within their communities. The Agrovets had been selected earlier in consultation with the farmers.

The maximum loan amount was set at Ksh 10,000, or $100, which was deemed sufficient to provide improved inputs for maize production for one acre for one season. For the RCC group, the Ksh 1,400 insurance premium (14%) was added to the base loan[3]. The premium was automatically transferred to the local insurance firm[4]. The interest rate applied to the loan balance was 14%/year[5].

2.4 Credit rationing and risk rationing

We adapted and modified the direct elicitation method proposed by Boucher et al., (2009) and applied by Verteramo-Chiu et al., (2014) to capture households' rationing status and the process is illustrated by Shee et al (2018). We asked the respondents a set of credit-related questions and used the responses to rate and group them into three groups namely: (1) **unconstrained** also called **price rationed** consisting of farmers who either were being

---

[3] The original design followed that proposed in Shee and Turvey (2012) who proposed that the insurance premium be added to the interest rate and prorated over the life of the loan (approximately 9 months). However, in this instance the insurer demanded that the premium be paid up-front. This increased the total cost of RCC by the accumulation of compound interest on the insurance premium over the life of the loan.

[4] Loan amounts and premiums were adjusted for farmers receiving an insurance 'subsidy'. The subsidy amount was transferred directly from project funds to the insurer.

[5] The interest rate was the base interest rate applied to all loans at the time. Since RCC was based on the accumulation of rainfall throughout the 'long-rain' season (October 15th to January 15th) there were concerns by the lender that failure of rains did not constitute the entirety of credit risks faced by the bank. Consequently, it was required that project funds be used to provide a 100% guarantee of all loans originated. These funds had to be deposited on account before any loans (traditional or RCC) could be made.

approached by banks to take credit, would normally receive full credit they applied for or did not have a demand for credit since they are not capital constrained, (2) **quantity rationed** implying a supply-side rationing where farmers either get less credit than their demand or they are denied credit altogether and (3) **risk rationed** comprising of farmers who excuse themselves from the credit markets due to fear of losing collateral or other implications of defaulting on loan repayment. Out of the total sample, 48% were unconstrained, 11% were quantity rationed and 41% were risk rationed. As illustrated in Figure 3, random assignment resulted in a reasonable consistency of rationing typologies across treatment and control groups.

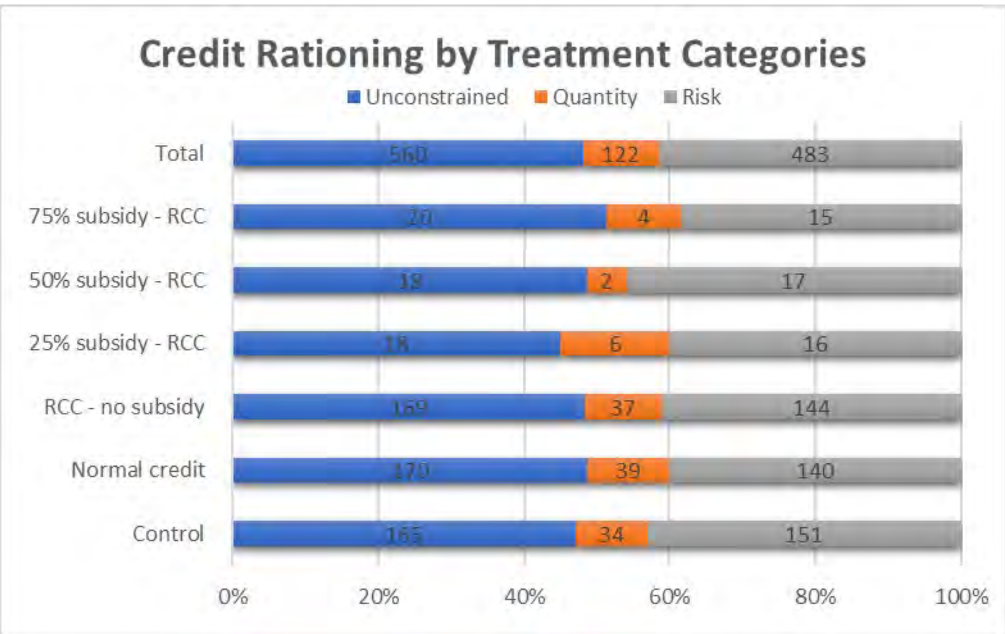

Figure 3: Credit rationing groups disaggregated into control and treatment categories

2.5 Households' socio-economic characteristics

Socio-economic characteristics of the sample are provided in Table 1. Consistent with randomized treatments, we find that traditional credit and RCC households were similar on all the baseline characteristics as shown by p-values columns of Table 1. 48% of the households were credit unconstrained, 11% were quantity rationed and 41% were risk rationed. 71% of the sampled households were represented in the initial training that was offered to explain the products as well as offer some financial literacy and tips on good maize agronomic practices. 66% of the household heads were practicing crop production as their main occupation while only 2% were into livestock production as main their occupation. 79% of the household heads were male with an average age of 56 years and 8.6 years of formal education, which implies they had cleared at least primary school education. The average household size was 6 (5.8) persons, which is typical of rural households in Kenya (Bongaarts & Casterline, 2013). Dependency ratio was 80% implying that only 20% of the household members were of the working age, defined as anyone above 14 years old and below 65 years old. On average, they were spending Ksh 2,280 (USD 22.80) weekly on food, Ksh 4,560 (USD 45.60) monthly on other non-food but frequent items such as fuel, transport, etc, and Ksh 89,920 (USD 89.92) annually on other non-food low frequency items such as clothes, fees, medication, etc. They had access to 4 acres of land whereby most of it (3.83 acres) was own land, 0.14 acres were rented in and 0.03 was borrowed land. Generally, renting and borrowing in land is not a very common practice in the research areas. Half of this land was under maize. They had an annual maize production of 833kg per household. This translates to roughly 9 bags of 90kg each, which is the most common item used for storage and measuring cereals in Kenya. Maize took most of the labour in man-days with an average of 190-man days per year compared to beans which took 28 days only. 35% of the total farm labour was hired labour with the rest coming from family and exchange labour.

Respondents report that they spent roughly Ksh 4,000 (USD 40) annually on fertilizer. All animals/livestock in the household summed up to roughly 7 tropical livestock unit (TLU)[6], which was valued at Ksh 86,190 (USD 861.90) and earned the households Ksh 13,540 (USD 135.40) annually. Households were represented in at least two social groups within the community. Access to extension in this area is very low with an average score of 1.12 out of possible 8. On a subjective welfare scale of 1 (very bad) to 5 (very good), the households scored an average of 2.78 ~3 which puts them at the middle of the scale. This means that, on average, respondents viewed their economic condition as being neither good nor bad in the local context.

To determine risk attitudes, we included in the baseline survey a simple experimental game following Binswanger (1980). First, respondents were rewarded with Ksh 300 (equivalent to average daily wage for the region) for their time. They were then asked if they wanted to risk their reward by participating in a risk game with potentially higher or lower returns, depending on the outcome of tossing a coin once. 99% agreed to participate in the risk

[6] To estimate TLU ownership per household, we mostly relied on Chilonda & Otte (2006) livestock units conversion table. The TLU column was calculated as a product of the number of animals owned by the households per species and its respective exchange ratio/coefficient in the TLU conversion table. Some species in the data collected were however not present in Chilonda & Otte's (2006) table. In such cases, and since TLU conversions are based on animals' weight, we used the coefficients of the animals in the table whose weight is closest to them.

game. Those willing to take risk were then provided with five coin-tossing options to identify where a household stands from being extremely risk-averse to preferring risk or being neutral. Following Binswanger's (1980) risk aversion classification, the average constant relative risk aversion score was 0.4 which indicate that on average, the households were moderately risk-averse.

Table 1: Comparing baseline means between control and treatment categories

	Control versus all credits			Traditional credit versus RCC			Full sample (n=1170)
	Control (n=351)	All credits (n=819)	p-value	Traditional credit (n=351)	All RCC groups (n=468)	p-value	
Unconstrained	0.47	0.48	0.679	0.48	0.49	0.904	0.48
	(0.50)	(0.50)		(0.50)	(0.50)		(0.50)
Quantity rationed	0.10	0.11	0.573	0.11	0.11	0.765	0.11
	(0.30)	(0.31)		(0.31)	(0.32)		(0.31)
Risk rationed	0.43	0.41	0.447	0.41	0.4	0.755	0.41
	(0.50)	(0.49)		(0.49)	(0.49)		(0.49)
Attended initial training and lotteries	0.75	0.69	0.026	0.67	0.72	0.166	0.71
	(0.43)	(0.46)		(0.47)	(0.45)		(0.45)
Crop production is household head main occupation	0.7	0.64	0.028	0.64	0.64	0.983	0.66
	(0.46)	(0.48)		(0.48)	(0.48)		(0.47)
Livestock rearing is household head main occupation	0.01	0.02	0.277	0.03	0.02	0.299	0.02
	(0.12)	(0.15)		(0.16)	(0.13)		(0.14)
Household head education level	8.63	8.62	0.969	8.6	8.66	0.814	8.63
	(4.04)	(3.74)		(3.78)	(3.70)		(3.83)
Male household head	0.77	0.79	0.57	0.79	0.79	0.766	0.79
	(0.42)	(0.41)		(0.41)	(0.40)		(0.41)
Age of household head	56.54	56.05	0.562	56.56	55.36	0.192	56.19
	(13.71)	(12.99)		(12.67)	(13.39)		(13.21)
Household size	5.79	5.74	0.752	5.69	5.81	0.491	5.76
	(2.41)	(2.32)		(2.26)	(2.40)		(2.35)
Dependency ratio	87.36	76.57	0.045	76.72	76.37	0.946	79.84
	(87.76)	(73.43)		(76.82)	(68.71)		(78.18)
Household dietary diversification index	10.36	10.32	0.58	10.35	10.28	0.313	10.33
	(0.94)	(0.98)		(0.96)	(1.01)		(0.97)
Weekly expenditure on food (Ksh "000")	2.26	2.29	0.723	2.28	2.3	0.852	2.28
	(1.19)	(1.15)		(1.12)	(1.19)		(1.16)
Expenditure on non-food items last 30 days (Ksh "000")	4.89	4.41	0.168	4.33	4.53	0.587	4.56
	(5.38)	(5.44)		(6.10)	(4.42)		(5.42)
Expenditure on non-food items last 12 months (Ksh "000")	82.81	92.97	0.257	88.94	98.34	0.489	89.92
	(108.90)	(195.26)		(204.21)	(182.80)		(173.93)
Total land accessed (acre)	3.71	4.13	0.27	4.34	3.85	0.393	4

	(4.19)	(8.91)		(11.12)	(4.53)		(7.80)
Land owned by household (acre)	3.56	3.95	0.306	4.15	3.69	0.421	3.83
	(4.16)	(8.90)		(11.10)	(4.53)		(7.79)
Land rented in (acre)	0.13	0.14	0.708	0.14	0.14	0.892	0.14
	(0.54)	(0.58)		(0.64)	(0.48)		(0.57)
Borrowed in land (acre)	0.02	0.04	0.34	0.05	0.02	0.218	0.03
	(0.20)	(0.41)		(0.53)	(0.17)		(0.36)
Per capita land ownership (acre)	0.76	0.88	0.364	0.97	0.77	0.384	0.85
	(0.93)	(3.68)		(4.76)	(1.17)		(3.12)
Land under seasonal crop (acre)	0.96	1.46	0.081	1.73	1.1	0.182	1.31
	(2.12)	(7.62)		(9.88)	(2.30)		(6.49)
Area under maize (acre)	2.00	2.04	0.730	2.025	2.055	0.817	2.025
	(1.84)	(2.03)		(2.20)	(1.77)		(1.97)
Annual maize production (kg)	832.27	833.06	0.991	792.96	886.52	0.281	832.82
	(957)	(1,241)		(1,278)	(1,189)		(1,163)
Annual maize labour (man day)	185.5	192.31	0.516	187.37	198.89	0.414	190.27
	(150.27)	(192.73)		(170.91)	(218.56)		(181.01)
Annual beans labour (man days)	27.5	27.86	0.875	26.2	30.08	0.244	27.75
	(31.75)	(43.87)		(32.21)	(55.72)		(40.60)
Percent of hired labour	33.02	36.15	0.155	35.2	37.4	0.377	35.21
	(34.07)	(34.98)		(34.22)	(35.99)		(34.73)
Annual total expenditure on fertilizer (Ksh "000")	4.10	3.93	0.68	3.84	4.06	0.58	3.98
	(6.30)	(5.67)		(5.31)	(6.12)		(5.86)
Tropical livestock unit	8.16	6.06	0.63	5.31	7.06	0.634	6.69
	(75.40)	(48.43)		(36.36)	(60.95)		(57.83)
Value of animals in household	78.9	89.31	0.101	87.48	91.74	0.641	86.19
	(80.62)	(133.43)		(145.56)	(115.44)		(120.11)
Total revenue from animals	8.85	15.55	0.017	13.55	18.21	0.404	13.54
	(23.81)	(71.26)		(40.75)	(98.19)		(61.10)
Social groups/network index	2.32	2.32	1.000	2.31	2.33	0.707	2.32
	(1.02)	(0.93)		(0.92)	(0.95)		(0.96)
Extension services access index	1.24	1.07	0.187	1.11	1.01	0.496	1.12
	(2.10)	(2.03)		(2.03)	(2.03)		(2.05)
Subjective economic welfare	2.82	2.78	0.353	2.76	2.8	0.44	2.79
	(0.62)	(0.66)		(0.68)	(0.63)		(0.65)
Household went a whole day without food	0.05	0.04	0.625	0.05	0.02	0.114	0.04
	(0.37)	(0.29)		(0.34)	(0.21)		(0.32)
Constant Relative Risk Aversion (CRRA) score	0.4	0.4	0.904	0.41	0.4	0.765	0.4
	(0.24)	(0.22)		(0.23)	(0.22)		(0.23)

3.0 Empirical framework

Since the assignment of treatments was randomized, the empirical strategy to establish the drivers of credit uptake avoids problems of endogeneity and justifies a distributional assumption of normality (Angrist & Pischke, 2008; Cameron & Trivedi, 2010; Cole et al., 2013; Giné & Yang, 2009; Karlan et al., 2011; Soderbom et al., 2015). Consequently, we investigate credit uptake with the binomial Probit model.

We first estimate a univariate Probit model to measure the treatment (RCC) effect on the uptake (uptake = 1, otherwise = 0), using treatment dummies as predictor variables. Because of the randomization process these treatment variables are the only source of uncommon exogenous variation and are thus valid instruments (Angrist & Pischke, 2008; Soderbom et al., 2015).

The Probit model follows Soderbom et al., (2015):

$$(1) \qquad \Pr(y_i = 1 \,|T_i) = \Phi(\beta T_i + \varepsilon_i)$$

Where y is loan uptake which takes a value of 1 if a household accepted the credit offer and 0 otherwise; T is a factor variable representing treatment dummies which takes a value of 1 if a household 'i' was either in RCC or RCC plus subsidies and 0 if in traditional credit; and β is the unknow treatment effect which we seek to estimate. The symbol Φ identifies a Probit estimator stochastic error term (ε) that is assumed to be normally distributed. A similar model was applied by (Cole et al., 2013) and Karlan et al. (2011) in their investigations into the determinants of uptake of credit bundled with index insurance policies.

Second, we likewise estimate a similar univariate Probit model to establish the effect of credit rationing on uptake:

$$(2) \qquad \Pr(y_i = 1 \,|R_i) = \Phi(\beta R_i + \varepsilon_i)$$

In this model, R is a factor variable that takes the value of 1 if a household 'i' is either quantity or risk rationed and 0 if unconstrained. β is the unknown effect of rationing on the uptake that we seek to establish.

Third, to determine the drivers of uptake, we extend the models by relaxing restrictions on individual household characteristics and estimate the multivariate binomial Probit model:

(3) $\Pr(y_i = 1 \,|\mathrm{T}_i R_i x_i) = \Phi(\beta_1 \mathrm{T}_i + \beta_2 R_i + \beta_3 x_{1i} + \cdots + \beta_k x_{ki} + \varepsilon_i)$

where x is a vector of household and farm characteristics (1,2, …, k) added to the model to examine the drivers of uptake and $\beta_1, \beta_2, \beta_3, \ldots \beta_k$ are their estimated coefficients.

Finally, to determine the determinants of credit rationing, we estimate a multinomial Probit model of the form:

(4) $\Pr(y_i = j|x_i) = \Phi(\beta_{1j} x_{1ij} + \cdots + \beta_{kj} x_{kij} + \varepsilon_i)$

Where y represents our categorical outcome variable with j categories, i.e. price, quantity and risk rationed, x is a k element vector of the determinants of rationing included in the estimation, and Φ indicates the multinomial normal distribution assumption of the error term and hence a multinomial Probit model.

4.0 Results and discussions

4.1 Credit Uptake

Based on the conventional wisdom about linked or bundled credit, our results are quite surprising. Overall, 819 farmers were offered credit, either traditional or RCC. Despite a perception of heightened demand for credit, only 33% (267) accepted the credit offer. Two factors likely played a significant role in their decisions. The first was that the loans were restricted to agricultural practices and could not be used for any other purpose. The second factor could be a week or two delay in loan distribution which may have discouraged some farmers from taking a loan.

The larger surprise was the determination that the difference in loan uptake was not substantially different among the treatments with 30% uptake among the traditional credit farmers and an average of 32% among the RCC categories (RCC with and without subsidies). Among the RCC farmers, those offered insured credit with a 25% subsidy on premium had the highest uptake at 37% followed by RCC without any subsidy and with 50% subsidy which tied at 35%. The lowest uptake was with RCC combined with 75% subsidy at barely a quarter (23%). These results suggest that credit demand is more inelastic than we thought. An overriding consideration is that the majority of participants had never received a formal loan before and so there was significant pent-up demand for credit of any type. In other words, the shadow price of the liquidity constraints facing these farmers was sufficiently higher than the cost of credit even with the additional charge of RCC, which corroborates some existing literature such as Barry et al (1981).

Further, we compare uptake among the credit rationing groups. The unconstrained and quantity rationed farmers had markedly higher uptake than risk rationed farmers, and this was significant at 5%. The unconstrained and quantity rationed farmers' uptake tied at 35% while risk rationed uptake was at 29%. (Fig 4)

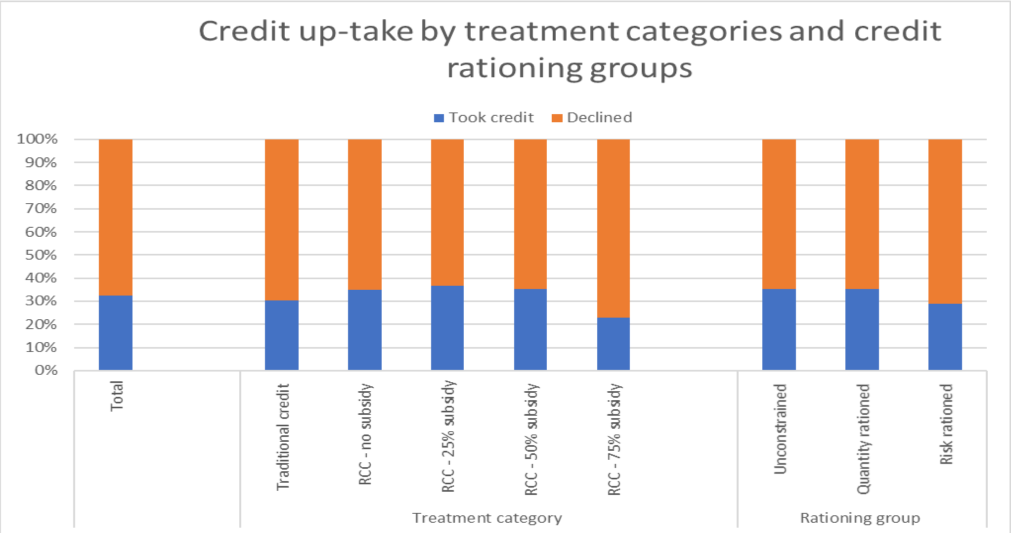

Figure 4: Uptake descriptive - by treatment categories and rationing group

4.2 Effect of treatment on the uptake

To estimate the effect of RCC on up-take, we estimated binary univariate and multivariate Probit models with uptake = 1 and declined credit = 0 on the left hand and treatment dummies on the right. Traditional credit was considered as the base category. When we ran a univariate model, uptake of all RCC credit types was not significantly different from traditional credit. However, with a multivariate model, which controls for endogeneity and hence more precise, we find a positive and significant effect of RCC without subsidy on uptake. This implies that holding all other factors constant, farmers offered RCC without subsidy were more likely to take the credit than farmers offered traditional credit. This has a marginal effect of 0.068 indicating that RCC without subsidy increased uptake by roughly 7%. Uptake of RCC combined with different levels of subsidies on premium was not significantly different from the uptake of traditional credit as shown in Table 2. We had also tried to compare uptake of RCC with and without subsidies and still the difference was not statistically significant. It is possible that among the up-takers, demand and motivation for credit overshadowed pricing conditions. (T**able 2)**. We later conducted a sensitivity analysis where we repeated the model with baseline controls but dropping the subsidy groups. We see consistent result on the treatment effect on uptake where RCC without subsidies increased uptake likelihood by 6.6%~7% and is still significant at 10%. **Annex:1**

As mentioned, we found these results puzzling. The point of the sub-experiment, albeit smaller than the whole with only 39 subsidy offers for each of three subsidy levels (N=117), was to obtain some insight into the elasticity of the risk premium when linked to credit. These results suggest that not only is the demand for insurance-linked credit highly inelastic, but that the added value of linking insurance to credit may not be as strong as we had originally thought. Subsequent work, as yet unpublished, employed a Choice Experiment on a random sample of the original subjects. Those results suggest that the demand is not as inelastic as this sub-experiment implies. Nevertheless, these results remind us that the enthusiasm that often accompanies results from theory ought to be dampened when that theory is put to practice.

Table 2: The effect of treatment on credit uptake

	Probit coefficients		Margins	
With baseline controls	No	Yes	No	Yes
Traditional credit				
RCC - no subsidy	0.126	0.191*	0.046	0.068*
	(0.10)	(0.10)	(0.04)	(0.04)
25% subsidy - RCC	0.168	0.213	0.061	0.076
	(0.21)	(0.21)	(0.08)	(0.08)
50% subsidy - RCC	0.129	0.282	0.047	0.103
	(0.22)	(0.24)	(0.08)	(0.09)
75% subsidy - RCC	-0.226	-0.261	-0.074	-0.082
	(0.23)	(0.24)	(0.07)	(0.07)
Constant	-0.511***	-1.708***		
	-(0.07)	-(0.64)		

4.3 Effect of credit rationing on up-take

As already reported in section 4.1, credit up-take was similar among unconstrained and quantity rationed households, both at 35%, while the uptake among the risk rationed was 29%. To statistically examine the effect of credit rationing on uptake, we estimated a binary Probit model with uptake on the left hand and rationing on the right. Unconstrained was the omitted base category for the rationing groups. We find that quantity rationing has a positive effect on uptake although this is neither substantial (negligible marginal effect) nor statistically significant. However, the positive sign implies that farmers who are quantity rationed are potentially more likely to take credit if offered compared to their unconstrained counterparts. This was in line with our priori expectation and the existing theory that quantity constrained farmers have positive notional demand for credit, but they receive less or zero supply. Offered a credit facility, as was done with this RCT, this group of farmers will eventually have effective demand.

As expected, risk rationing has a negative effect on uptake, and this was statistically significant at 10%. This implies that risk rationed farmers were less likely to take the offered credit compared to their unconstrained colleagues. From the marginal effect column, being risk rationed reduced the probability of uptake by 6.3%. This again is in line with existing theory that even when provided with an income enhancing credit contract, a risk rationed farmer chooses to withdraw from the credit market and instead undertakes a less return but more certain/less risky venture. This is due to the fear of the risk of losing collateral or undergoing other defaulting implications. **(Table 3)**

RCC was designed to solve this pre-existing risk rationing condition. However, this may not have been achieved with this first implementation phase since the implementing lender required collateral in line with any traditional loan offered by the bank. This will be explored further in subsequent research, but it is worth noting at this point that although risk-rationed farmers accepted traditional credit at a lower rate than RCC, they did nonetheless accept traditional credit. The essential argument in Boucher et al (2009) is that while farmers may have a demand for credit they do not, or cannot, act upon it, resulting in distortions in the rural credit system. Verteramo-Chiu et al (2014) support this view. In our RCT we use the same direct elicitation and identification approach used in these studies so the relatively high uptake of traditional credit by the risk-rationed group comes as some surprise. One possible explanation is a finding in Verteramo-Chiu et al (2014) that the credit demand elasticity of risk-rationed farmers increases as interest rates fall. The base interest rate of 14% actually applied to traditional loans in this RCT may have breached the high inelasticity that comes with higher interest rates on informal loans and rotating savings and credit associations (ROSCA) in the Machakos region which had interest rates as high as 100% according to farmers in focus groups. The relatively low interest rate of 14% could therefore encourage even risk-rationed farmers to borrow. A promising avenue to pursue is an exploration of risk-rationing in the presence of binding liquidity constraints. A starting point might be the proposition that for some risk-rationed farmers, the shadow price of binding liquidity constraints is so high, that the utility gain from relaxing those constraints exceeds the disutility that comes from a natural aversion to borrowing.

Table 3: Effect of risk rationing on credit uptake

UP_TAKE	Coef.	p-value	Marginal effect	p-value
Unconstrained	0.000	.		
Quantity rationed	0.001	0.995	0.0004	0.995
	(0.15)		(0.06)	
Risk rationed	-0.176*	0.072	-0.0627*	0.070
	(0.10)		(0.03)	
Constant	-0.38***	0.000		
	(0.07)			
Mean dependent var	0.326	SD dependent var		0.469
Pseudo r-squared	0.003	Observations		815
Chi-square	3.539	Prob > chi2		0.17

*** p<0.01, ** p<0.05, * p<0.1, Standard errors are in parenthesis

4.4 The drivers of uptake

In this section, we present the drivers of uptake from the Probit multivariate estimation described in section **4.2** above. Later, we dropped credit rationing and repeated the model to eliminate endogeneity that may arise since the same household characteristics may influence both rationing and uptake. The results from both models were however consistent. To avoid falling into the dummy-trap problem, we omitted the first categories for both treatment and rationing groups; namely traditional credit and unconstrained respectively.

The direction of the relationship between the rationing groups and uptake still holds as explained earlier but this time, after including household characteristics covariates, even risk rationing is not statistically significant. Compared to unconstrained households, quantity rationed households were 4.5% more likely to take the credit offered while risk rationed households were 4% less likely to take.

Training attendance increased uptake probability by 19% and was significant at 1%. A household was 7.4% more likely to take up the credit if the household head's main occupation was crop production. This was significant at 5%. In the estimation excluding rationing, uptake probability increased by 3% with a Ksh. 1000 (USD 100) increase in weekly food consumption. Land ownership was negatively correlated to uptake where increment in own land size by one acre reduced uptake probability by 0.5% when rationing was included, and 0.4% when rationing was excluded from the estimation. Additionally, an increase of hired farm labour by 1% increased uptake likelihood by 0.1% and this was significant at 10%. Revenue from livestock had a positive effect on uptake. An increment of annual revenue from animals by Ksh

1000 increased uptake likelihood by 0.04%. This may not be substantial but was significant at 5%. **(Table 4)**

Table 4: Drivers of credit uptake for all categories combined

	Uptake model with credit rationing		Uptake model without credit rationing	
	Probit model	Margins	Probit model	Margins
Unconstrained				
Quantity rationed	0.123	0.045		
	(0.16)	(0.06)		
Risk rationed	-0.059	-0.021		
	(0.11)	(0.04)		
Traditional credit				
RCC - no subsidy	0.191*	0.068*	0.182*	0.065*
	(0.10)	(0.04)	(0.10)	(0.04)
25% subsidy - RCC	0.213	0.076	0.197	0.071
	(0.21)	(0.08)	(0.21)	(0.08)
50% subsidy - RCC	0.282	0.103	0.267	0.097
	(0.24)	(0.09)	(0.24)	(0.09)
75% subsidy - RCC	-0.261	-0.082	-0.265	-0.083
	(0.24)	(0.07)	(0.24)	(0.07)
Attended initial training and lotteries	0.531***	0.190***	0.539***	0.193***
	(0.11)	(0.04)	(0.11)	(0.04)
Crop production is household head’s main activity	0.207**	0.074**	0.206**	0.074**
	(0.11)	(0.04)	(0.10)	(0.04)
Household head education level	0.006	0.002	0.007	0.003
	(0.02)	(0.01)	(0.02)	(0.01)
Male household head	0.128	0.046	0.137	0.049
	(0.13)	(0.05)	(0.13)	(0.05)
Age of household head	-0.001	0.000	-0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Dependency ratio	-0.001	0.000	-0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Household dietary diversification index	0.006	0.002	0.002	0.001
	(0.05)	(0.02)	(0.05)	(0.02)
Weekly expenditure on food (Ksh “000”)	0.068	0.024	0.073*	0.026*
	(0.04)	(0.02)	(0.04)	(0.02)
Land owned by household	-0.013*	-0.005*	-0.013*	-0.004*
	(0.01)	(0.00)	(0.01)	(0.00)
Area under maize (acre)	0.007	0.002	0.006	0.002
	(0.01)	(0.01)	(0.01)	(0.01)
Annual maize production (kg)	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)

Percent of hired labour	0.003*	0.001*	0.003*	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)
Total revenue from animals	0.001**	0.004**	0.001**	0.004**
	(0.00)	(0.00)	(0.00)	(0.00)
Social groups/network index	0.038	0.014	0.041	0.015
	(0.05)	(0.02)	(0.05)	(0.02)
Extension services access index	0.038	0.014	0.041*	0.015*
	(0.02)	(0.01)	(0.02)	(0.01)
Subjective economic welfare	0.043	0.015	0.036	0.013
	(0.08)	(0.03)	(0.08)	(0.03)
Household went a whole day without food	-0.155	-0.056	-0.147	-0.053
	(0.17)	(0.06)	(0.17)	(0.06)
Constant relative risk aversion (CRRA) score	0.045	0.016	0.054	0.019
	(0.21)	(0.08)	(0.21)	(0.08)
Constant	-1.708***		-1.685***	
	(0.64)		(0.62)	
Observations	793	793	797	797
Log likelihood	-473.228		-475.63	
AIC	996.455		997.26	

* p<0.10, ** p<0.05, *** p<0.01

4.5 Drivers of credit rationing

To determine the factors that drive credit rationing among the households, we used multinomial Logit and multinomial Probit models with rationing as the output variable and household characteristics as the predictor variables. The price rationed or unconstrained group was the base category and therefore we interpret our results in reference to it. We find consistent results from both estimators with small differences in estimated coefficients. Since the coefficients are from non-linear models and marginal effects are not included in the table, we only interpret the nature and significance of the relationships but not the magnitude.

Uptake difference between the unconstrained and the quantity rationed was significantly affected by only 4 out of 16 factors, two positively and two negatively correlated. Quantity rationing increased with dependency ratio and weekly food expenditure while the same reduced with household dietary diversification index and subjective welfare. This implies that households with more dependants than works and those who spend most of their income on food were more likely to be denied credit or get less than demanded. We reason that, as the number of dependants in a household increases while holding income constant, the proportion of income that goes to food increases. This leaves the household with less surplus funds which can be put into loan repayment and hence their demand for credit, at best, is likely to be met with less supply, or at worst, be turned down. The situation is likely to get worse if dependency increment and income reduction occur simultaneously, which is not foreign to rural households especially with death of heads, spouses and/or other working household members. Dietary diversification and subjective economic welfare are both indices of wellbeing of a household and as expected, as a household's wellbeing improves, the chances of their credit demand being met also increases. These findings also confirm that in the appraisal process, banks collect information related to households' size, income and welfare indicators and consider them when making credit-worthiness verdicts.

On the other hand, risk rationing was significantly affected by 10 out of 16 factors selected in the model. The households whose heads were into agriculture as their main occupation, either crop production or livestock rearing were less likely to be risk rationed, which implies that they were more likely to apply for credit. In rural areas, farming is the main source of income. Those not into farming as their main occupation are mostly into low income casual jobs and therefore have no income generating ventures to apply credit against and for. A few are into other businesses which still rely on the welfare of the farming households. Risk rationing also reduced with household head's level of education but increased with his/her age. This indicates that households with younger and more educated heads were less likely to be risk rationed and hence would have an effective demand for credit. Risk rationing increased with dependency ratio, suggesting that households with more dependents than workers were more likely to be risk rationed than households with fewer dependants. Risk rationing also reduced with dietary diversification index and expenditure on food. This insinuates that households who spent more on food and whose consumed more diversified foods were less likely to be risk rationed. This is unlike quantity rationing which increased with food expenditure meaning that households spending more of their income on food do apply for credit more than those who spend less, but they are more likely to be denied credit more than those who spend less on food. Further, risk rationing reduced with land ownership, hired farm labour and household's representation and participation in social groups and/or other social networks within the community. **(Table 5)**

Table 5: Factors of credit rationing - multinomial Logit and Probit with unconstrained as the base category

	Quantity rationed		Risk rationed	
	Logit	Probit	Logit	Probit
Crop production is household head main activity	-0.219	-0.169	-0.328**	-0.272**
	(0.23)	(0.16)	(0.15)	(0.13)
Livestock rearing is household head main activity	-0.148	-0.206	-1.273**	-1.031**
	(0.63)	(0.46)	(0.55)	(0.43)
Household head education level	-0.025	-0.024	-0.050**	-0.042**
	(0.03)	(0.02)	(0.02)	(0.02)
Male household head	0.385	0.221	-0.197	-0.163
	(0.30)	(0.20)	(0.18)	(0.15)
Age of household head	0.006	0.004	0.011**	0.010**
	(0.01)	(0.01)	(0.01)	(0.01)
Dependency ratio	0.002*	0.002*	0.002**	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
Household dietary diversification index	-0.299***	-0.226***	-0.205***	-0.171***
	(0.11)	(0.08)	(0.08)	(0.06)
Weekly expenditure on food	0.135*	0.087	-0.141**	-0.116**
	(0.08)	(0.06)	(0.06)	(0.05)
Land owned by household	-0.003	-0.006	-0.056***	-0.044***
	(0.01)	(0.01)	(0.02)	(0.02)
Percent of hired labour	-0.003	-0.002	-0.003*	-0.003*
	(0.00)	(0.00)	(0.00)	(0.00)
Tropical livestock unit (TLU)	-0.049	-0.034	0.000	0.000
	(0.04)	(0.02)	(0.00)	(0.00)
Social groups/network index	0.059	0.019	-0.179**	-0.150**
	(0.11)	(0.08)	(0.07)	(0.06)
Extension services access index	-0.067	-0.048	-0.023	-0.02
	(0.05)	(0.03)	(0.03)	(0.03)
Subjective economic welfare	-0.328*	-0.222*	-0.175	-0.148
	(0.18)	(0.12)	(0.11)	(0.09)
Household went a whole day without food	0.092	0.069	-0.186	-0.152
	(0.24)	(0.19)	(0.22)	(0.18)
Constant relative risk aversion (CRRA) score	-0.363	-0.282	-0.161	-0.145
	(0.45)	(0.31)	(0.29)	(0.24)
constant	2.064*	1.731**	3.679***	3.063***
	(1.24)	(0.87)	(0.88)	(0.73)

4.6 Conclusions

Weather related risks, particularly drought, is among the major hurdles facing smallholder farmers in Kenya. This is further compounded by capital constrictions, credit inaccessibility and existing credit rationing and risk rationing conditions. There has been much work done towards developing and promoting technologies and practices to help farmers cope with drought, but inadequate capital and lack of weather risk hedging make it hard for small holders to adopt them. To manage drought risk and to improve access to credit, we developed a market-based solution that bundles rainfall index insurance and agricultural credit and implemented a randomized controlled trial with 1170 households. We assess farmers' credit rationing, its determinants and effects on credit uptake. We also assess the effects of bundling weather index insurance on credit uptake as well as the determinants of credit uptake, including the influence of farm level characteristics.

We find that 48% of the households were price-rationed/unconstrained, 41% were risk-rationed and 11% were quantity-rationed. With reference to price-rationed or unconstrained households, quantity rationing probability increased with dependency ratio and weekly food expenditure while the same reduced with household dietary diversification index and subjective welfare. Risk rationing probability on the other hand increased with age of the household head and dependency ratio and reduced with crop production and livestock rearing being the household head's main occupation, household head's education level, dietary diversification index, weekly expenditure on food, land ownership and hired labour.

The average credit uptake rate was 33% with the uptake of bundled credit being significantly higher than that of traditional credit. Premium subsidies did not affect uptake significantly insinuating that the need for credit among those who decided to take was high and the price differences in credit and insurance did not affect their decision. Risk rationing seems to influence the credit uptake negatively. RCC was designed to particularly deal with risk rationing where farmers fail to take credit due to fear of losing their asset or hampering consumption to pay for credit in case their investment fails to yield due to drought. Other non-random socio-economic factors which were significantly associated with uptake are, training attendance, crop production being the main household head occupation, expenditure on food, hired labour, livestock revenue and access to credit which had a positive correlation to credit uptake and land ownership which was negatively correlated to uptake.

While these results provide very important insights into credit behaviour and demand of subsistence farmers, our study came with some surprises. The first is our finding that farmers self-identified as being risk-rationed accepted traditional credit at a lower, but only slightly so, rate than RCC. Risk-rationing was a key driver of the RCT with the premise being that RCC would be substantially more attractive than traditional credit. Our reliance on risk-rationing as a motive might have been over-stated. Our sub-experiment which provided insurance subsidy to 117 farm households had a near-insignificant effect suggesting that the demand for the insurance component of RCC is highly inelastic. We have suggested that the opportunity costs of binding liquidity constraints may have been so high that the costs of traditional or risk-contingent credit were low in comparison, and that this liquidity effect might dominate the risk-rationing effect. Further research along these lines is warranted.

References

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly Harmless Econometrics : An Empiricist's Companion. Massachusettts I nstitute of Technology and The London school of Economics*.

Barnett, B. J., & Mahul, O. (2007). Weather index insurance for agriculture and rural areas in lower-income countries. *American Journal of Agricultural Economics*, *89*(5), 1241–1247.

Barrett, C. B., Barnett, B. J., Carter, M. R., Chantarat, S., Hansen, J. W., Mude, A. G, Osgood, D.E., Skees, J.R., Turvey, C.G. and Ward, M. N. (2007). *Poverty Traps and Climate Risk : Limitations and Opportunities of Index-Based Risk Financing. IRI Technical Report*.

Barry, P. J., Baker, C. B., & Sanint, L. R. (1981). Farmers' Credit Risks and Liquidity Management. *American Journal of Agricultural Economics*, *63*(2), 216–227.

Binswanger, H. P. (1980). Attitudes toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics*, *62*(3), 395–407.

Bongaarts, J., & Casterline, J. (2013). Fertility Transition: Is sub-Saharan Africa Different? *Population and Development Review*, *38*(1), 153–168.

Boucher, S. R., Carter, M. R., & Guirkinger, C. (2008). Risk rationing and wealth effects in credit markets: Theory and implications for agricultural development. *American Journal of Agricultural Economics*, *90*(2), 4709–423.

Boucher, S. R., Guirkinger, C., & Trivelli, C. (2009). Direct Elicitation of Credit Constraints: Conceptual and Practical Issues with an Application to Peruvian Agriculture. *Economic Development and Cultural Change*, *57*(4), 609–640.

Branca, G., Tennigkeit, T., Mann, W., & Lipper, L. (2011). *Identifying opportunities for climate-smart agriculture investments in Africa.* Rome.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics using Stata Revised Edition* (2nd ed.). College Station, Texas: Stata Press.

Carter, M., de Janvry, A., & Sadoulet, E. (2014). *Index-based weather insurance for developing countries: A review of evidence and a set of propositions for up-scaling* (Development Policies working paper 111).

Carter, M. R., Cheng, L., & Sarris, A. (2011). *The Impact of Inter-linked Index Insurance and Credit Contracts on Financial Market Deepening and Small Farm Productivity*. *Annual Meeting of the American Applied Economics Association*. Pittsburgh PA.

Chantarat, S., Barrett, C. B., Mude, A. G., & Turvey, C. G. (2007). Using weather index insurance to improve drought response for famine prevention. *American Journal of Agricultural Economics*, *89*(5), 1262–1268.

Chantarat, S., Mude, A. G., Barrett, C. B., & Turvey, C. G. (2017). Welfare Impacts of Index Insurance in the Presence of a Poverty Trap. *World Development*, *94*, 119–138.

Chantarat, S., Turvey, C. G., Mude, A. G., & Barrett, C. B. (2008). Improving humanitarian response to slow-onset disasters using famine-indexed weather derivatives. *Agricultural Finance Review*, *68*(1), 169–195.

Chilonda, P., & Otte, J. (2006). Indicators to monitor trends in livestock production at national, regional and international levels. *Livestock Research for Rural Development*, *18*(117).

Chiu, L. J. V., Khantachavana, S. V., & Turvey, C. G. (2014). Risk rationing and the demand for agricultural credit: A comparative investigation of Mexico and China. *Agricultural Finance Review*, *74*(2), 278–270.

Chodechai, S. (2004). *Determinants of bank lending in Thailand: An empirical examination for the years 1992--1996. Unpublished Thesis*. ZEF.

Cole, S., Bastian, G. G., Vyas, S., Wendel, C., & Stein, D. (2012). *The effectiveness of index-based micro-insurance in helping smallholders manage weather-related risks*. London.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to household risk management: Evidence from india. *American Economic Journal: Applied Economics*, *5*(1), 104–135.

Cummins, J. D., & Mahul, O. (2009). *Catastrophe Risk Financing in Developing Countries - Principles for Public Intervention*. *The World Bank*. Washington, DC.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, *96*(2), 159–173.

Dzadze, P., Mensah, O., R., A., & K., N. G. (2012). Factors determining access to formal credit in Ghana: A case study of smallholder farmers in the Abura-Asebu Kwamankese district of central region of Ghana. *Journal of Development and Agricultural Economics*, *4*(14), 416–423.

Farrin, K., & Miranda, M. J. (2015). A heterogeneous agent model of credit-linked index insurance and farm technology adoption. *Journal of Development Economics*, *116*, 199–211. https://doi.org/10.1016/j.jdeveco.2015.05.001

Giné, X., & Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidencefrom Malawi. *Journal of Development Economics*, *89*(1), 1–11.

Glauber, J. W. (2004). Crop insurance reconsidered. *American Journal of Agricultural Economics*, *86*(5), 1179–1195.

Jensen, N., & Barrett, C. (2017). Agricultural index insurance for development. *Applied Economic Perspectives and Policy*, *39*(2), 199–219.

Karlan, D., Kutsoati, E., McMillan, M., & Udry, C. (2011). Crop Price Indemnified Loans for Farmers: A Pilot Experiment in Rural Ghana. *Journal of Risk and Insurance*, *78*(1), 37–55.

Maloba, M., & Alhassan, A. L. (2019). Determinants of agri-lending in Kenya. *Agricultural Finance Review*, *79*(5), 598–613.

Marr, A., Winkel, A., van Asseldonk, M., Lensink, R., & Bulte, E. (2016). Adoption and impact of index-insurance and credit for smallholder farmers in developing countries: A systematic review. *Agricultural Finance Review*, *76*(1), 94–118.

Muhamma, A. S., & Jan, A. F. (2011). The Impact of Agricultural Credit on Agricultural Productivity in Dera Ismail Khan (District) Khyber Pakhtonkhawa Pakistan. *European Journal of Business and Management*, *3*(2), 1–7.

Oguzie, E. E., Onuoha, G. N., & Onuchukwu, A. I. (2005). Inhibitory mechanism of mild steel corrosion in 2 M sulphuric acid solution by methylene blue dye. *Materials Chemistry and Physics*, *89*(2–3), 305–311. https://doi.org/10.1016/j.matchemphys.2004.09.004

Pelka, N., Musshoff, O., & Weber, R. (2014). Does weather matter? How rainfall affects credit risk in agricultural microfinance. *Agricultural Finance Review*, *75*(2), 194–212.

Shee, A., Pervez, S., & Turvey, C. G. (2018). Heterogeneous Impacts of Credit Rationing on Agricultural Productivity: Evidence from Kenya. In *Agricultural & Applied Economics Association Annual Meeting*. Washington, DC.

Shee, A., & Turvey, C. G. (2012). Collateral-free lending with risk-contingent credit for agricultural development: Indemnifying loans against pulse crop price risk in India. *Agricultural Economics (United Kingdom)*, *43*(5), 561–574.

Shee, A., Turvey, C. G., & Woodard, J. (2015). A field study for assessing risk-contingent credit for Kenyan pastoralists and dairy farmers. *Agricultural Finance Review*, *75*(3), 330–348.

Shee, A., Turvey, C. G., & You, L. (2019). Design and rating of risk-contingent credit for balancing business and financial risks for Kenyan farmers. *Applied Economics*, *51*(50), 5447–5465.

Soderbom, M., Teal, F., Eberhardt, M., Quinn, S., & Zeitlin, A. (2015). *Empirical Development Economics*. London and New York: Routledge.

Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, *71*(3), 393–410.

Turvey, C. G. (2001). Weather Derivatives for Specific Event Risks in Agriculture. *Review of Agricultural Economics*, *23*(2), 333–351.

von Negenborn, F., Weber, R., & Musshoff, O. (2017). Explaining weather-related credit risk with evapotranspiration and precipitation indices. *Agricultural Finance Review*, *78*(2), 246–261.

Annex 1: Treatment effect on credit uptake - Sensitivity check by dropping subsidies

	Uptake model with credit rationing		Uptake model without credit rationing	
	Probit model	Margins	Probit model	Margins
Unconstrained				
Quantity rationed	0.067	0.024		
	(0.17)	(0.06)		
Risk rationed	-0.005	-0.002		
	(0.11)	(0.04)		
Normal credit				
RCC - no subsidy	0.185*	0.066*	0.177*	0.063*
	(0.10)	(0.04)	(0.10)	(0.04)
If attended the initial training and lot	0.481***	0.172***	0.490***	0.175***
	(0.12)	(0.04)	(0.12)	(0.04)
Crop production is household head main activity	0.218*	0.078*	0.214*	0.077*
	(0.11)	(0.04)	(0.11)	(0.04)
Household head education level	0.013	0.004	0.013	0.005
	(0.02)	(0.01)	(0.02)	(0.01)
Male household head	0.098	0.035	0.105	0.037
	(0.15)	(0.05)	(0.15)	(0.05)
Age of household head	0.001	0.000	0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Dependency ratio	-0.001	0.000	-0.001*	-0.000*
	(0.00)	(0.00)	(0.00)	(0.00)
Household dietary index	0.023	0.008	0.019	0.007
	(0.06)	(0.02)	(0.06)	(0.02)
Weekly expenditure on food	0.066	0.024	0.067	0.024
	(0.05)	(0.02)	(0.05)	(0.02)
Land owned by household	-0.020*	-0.007*	-0.02	-0.007
	(0.01)	(0.00)	(0.01)	(0.00)
Area under maize (acre)	0.006	0.002	0.004	0.001
	(0.02)	(0.01)	(0.02)	(0.01)
Annual maize production (kg)	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Percent of hired labour	0.002	0.001	0.002	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Total revenue from animals	0.001*	0.000*	0.001*	0.000*
	(0.00)	(0.00)	(0.00)	(0.00)
Social groups/network index	0.047	0.017	0.049	0.018
	(0.06)	(0.02)	(0.06)	(0.02)
Extension services access index	0.050**	0.018**	0.053**	0.019**
	(0.03)	(0.01)	(0.03)	(0.01)
Subjective economic welfare	0.108	0.039	0.105	0.038
	(0.09)	(0.03)	(0.09)	(0.03)

Household went a whole day without food	-0.107	-0.038	-0.103	-0.037
	(0.17)	(0.06)	(0.17)	(0.06)
CRRA score	-0.007	-0.003	0.003	0.001
	(0.23)	(0.08)	(0.23)	(0.08)
constant	-2.118***		-2.074***	
	(0.71)		(0.68)	
Observations	677	677	680	680
Log likelihood	-402.883		-404.434	
AIC	849.766		848.867	

* p<0.10, ** p<0.05, *** p<0.01