Chapter 12

TRANSFORMING FOOD SYSTEMS THROUGH RISK-CONTINGENT CREDIT IN RURAL AFRICA: DEVELOPMENT, EXPERIMENTATION, AND EVALUATION[1]

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Throughout Africa, climate change is posing severe challenges to agricultural production and food security. Agricultural risks—particularly those associated with drought—are a major cause of low agricultural productivity in most African countries, including Kenya. According to the Government of Kenya, four consecutive years (2008–2011) of drought caused US$12.1 billion in losses, accounting for about 8 percent of GDP, including losses in assets and disruptions to the economy across sectors (Kenya, Ministry of Agriculture, Livestock and Fisheries 2014). Currently, Kenya is in the middle of an acute drought following three consecutive poor rainy seasons. This has led to a drop in crop production nationally of about 70 percent, which has disproportionately exposed the communities of arid and semi-arid lands to hunger and malnutrition.

New technologies, such as improved crop varieties, fertilizers, and disease and pest control approaches, provide one avenue by which to increase productivity and improve farm incomes, hence reducing the vulnerability of farming households to drought and other shocks. Yet many farmers cannot access sufficient credit to adopt these technologies. Lenders in Kenya's credit markets limit the supply of credit to borrowers because of seemingly uninsurable weather

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risks tied to frequent failures in seasonal rainfall and related heat stress. In cases where farmers can access credit, loans are made under relatively high collateral restrictions, which farmers are reluctant to accept. Consequently, borrowers voluntarily withdraw from the credit market (risk rationing), which, in turn, suppresses incentives for lenders to expand financial services (quantity rationing). Ultimately, incomplete financial markets result in suboptimal, welfare-reducing credit access that forces most farmers—especially women farmers—to adopt low-risk, low-return activities. This, in turn, is considered a key driver of persistent poverty and jeopardizes food security (Barrett, Carter, and Chavas 2019; Santos and Barrett 2019).

There have been efforts by private sector financial institutions to expand credit access to farmers by setting up branches in rural areas, but frequent droughts across and within years put agricultural productivity at risk for many farms and regions simultaneously. Such covariate risks can stress lenders' portfolios through increased loan defaults and have been identified as a significant contributing factor in lenders' reluctance to offer credit to farmers. Additionally, the absence of insurance markets results in more inelastic credit demands and supplies than might otherwise occur with a targeted (for example, weather-based) insurance product in place. A fundamental hinderance to increasing the depth and breadth of more inclusive financial policies for farmers in drought-prone states is the absence of an effective risk-transferring mechanism that simultaneously addresses the problem of weather-related business risks facing farmers and the financial/credit risks facing lenders.

Over the past two decades, index insurance has been promoted to help farmers manage weather-related risks but low demand and uptake have hampered its utility (Turvey 2001; Binswanger 2012; Miranda and Farrin 2012; Marr et al. 2016; Cole and Xiong 2017; Jensen and Barrett 2017). Economists and practitioners are now turning their attention to new financially engineered approaches to the design and implementation of insurance programs that can be bundled with credit in a way that reduces the high default risk facing lenders when exposed to widespread droughts and other natural (or market) catastrophes (Shee and Turvey 2012; Gallenstein et al. 2019; Mishra et al. 2021a, 2021b).

To address these challenges, we developed an innovative, market-based credit solution referred to as risk-contingent credit (RCC). RCC is a financial product that embeds within its structure an insurance contract that, when triggered, offsets loan payments, providing a risk-efficient balance between business and financial risks. Because the insurance coverage substitutes for collateral, it is more financially inclusive than conventional credit and has the potential to bring quantity- and risk-rationed farmers into the credit market, with expected benefits from higher productivity and improved livelihoods.

This chapter presents the development and evaluation of RCC for smallholder farmers with a special focus on the innovative pre-experimental and experimental methods to develop, test, adapt, and evaluate the intervention. We describe the scientific bundling of insurance with credit, how we approached communicating the RCC concept with farmers and stakeholders, and ways we incorporated their feedback to incrementally co-develop the full RCC product and its subsequent implementation in Kenya. We also provide an overview of the impact evaluation of RCC through a variety of in-the-field activities, including formative evaluation through choice experiments, survey design, and a randomized controlled trial (RCT). The chapter concludes with a discussion of the broader implications of RCC and its potential for scale-up to contribute to transforming African food systems.

Development of risk-contingent credit for smallholder farmers

Drought-related climate risk is the largest source of risk to agricultural productivity and consumption in most of sub-Saharan Africa, including Kenya (Giné and Yang 2009; Dercon and Christiaensen 2011; Cole et al. 2012). Drought imposes a considerable and costly constraint on capital and wealth accumulation for those engaged in agricultural activities or with livelihoods tied to the well-being of the farming sector (Barrett et al. 2007). Credit access compounds this problem, especially among smallholder households that lack adequate collateral. This exacerbates both supply-side quantity rationing and demand-side risk rationing (Boucher, Carter, and Guirkinger 2008; Verteramo-Chiu, Khantachavana, and Turvey2014). Faced with high loan default risk, banks use restrictive lending policies such as high interest rates, harsh collateral requirements, and credit denial to those deemed risky borrowers, among others, which effectively crowd out smallholders from the credit fold (Stiglitz and Weiss 1981; Boucher, Carter, and Guirkinger 2008; Boucher, Guirkinger, and Trivelli 2009).

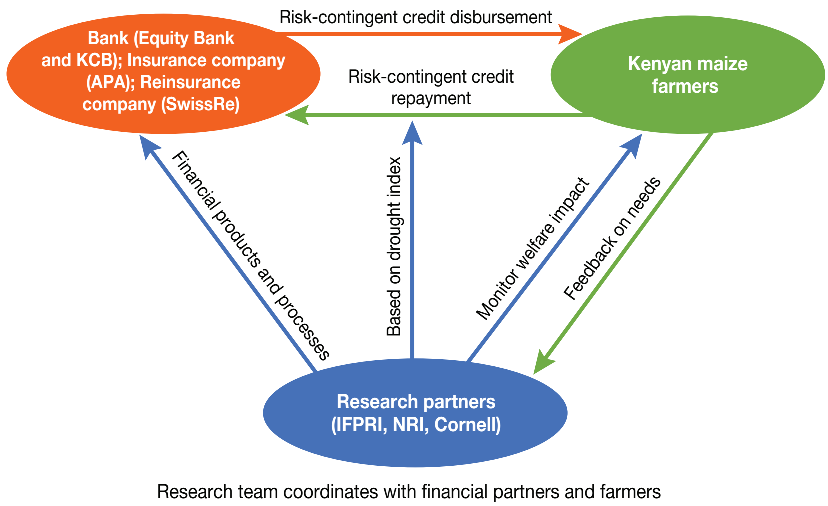
There have been efforts to mitigate the impacts of drought on agricultural productivity in this region, mostly by governments and donors. Most of them have been developed under the climate-smart agriculture umbrella, with adaptive capacity, sustainable intensification, and greenhouse gas mitigation as the main goals (Branca 2012). They range from conservation agriculture to stress-tolerant crop varieties, pest and disease management methods, promotion of adaptable alternative crops and animals, capacity building, and gender mainstreaming, as well as innovative ways of sharing the right information with farmers in a timely manner, mostly through mobile phones. Such interventions mostly aim to develop and promote new and efficient farming technologies and practices. However, the large economic cost of drought-related climate shocks (and, by extension, flooding in some regions) cannot be financed by government and the donor community alone. There is a need for market-based interventions to enhance farmers' capacity to capitalize on the benefits of agricultural technologies and/or practices and at the same time to provide them with protection against the major agricultural downside risks (Shee, Turvey, and You 2019; Ndegwa et al. 2020).

The idea behind the RCC mechanism is to avoid low uptake of agricultural insurance. The function of any insurance is to transfer (smooth) income across good and bad states. In dealing with poor agricultural farmers, the upfront payment of a premium in standard insurance not only imposes liquidity constraints but also transfers income across time (Casaburi and Willis 2018). Literature shows that liquidity issues and time preferences are important constraints to insurance uptake. By removing both the liquidity constraint and the effects of climate risk, the RCC mechanism can achieve better targeting of poorer farmers. Since insurance can substitute for collateral, the RCC mechanism has the potential to encourage otherwise risk-rationed farmers to take up RCC loans. And since the indemnity from the embedded insurance is applied to the underlying debt obligation, the RCC can reduce the probability of default and build trust that can boost uptake.

We designed RCC that bundles insurance with credit to achieve the dual advantages of coverage against covariate risks and enhanced adoption of technologies that would lead to improved livelihoods. Unlike standard indemnity- and index-based insurance products,[2] RCC does not require farmers to pay premiums upfront and out of pocket, and hence removes liquidity constraints and targets poorer farmers more effectively (Shee, Turvey, and You 2019). The insurance component with RCC substitutes for collateral and hence makes it more financially inclusive than conventional credit products. We developed and implemented RCC in Machakos county of Kenya in

2 With indemnity-based crop insurance, payouts are based on the actual losses experienced by the farmer, regardless of the cause. They are all-peril in nature and have high administrative costs because of the farm follow-up required to ascertain losses. On the other hand, the objective of weather index insurance is to establish a trigger below (or above) which the weather peril is highly correlated with yield loss. The most common index is based on cumulative rainfall, although other notable indices have been proposed, including average area yield, soil moisture, heat index, vegetation indexes such as the normalized difference vegetation index and enhanced vegetation index, and commodity prices (Ndegwa et al. 2022).

FIGURE 12.1 The RCC business model and institutional setup

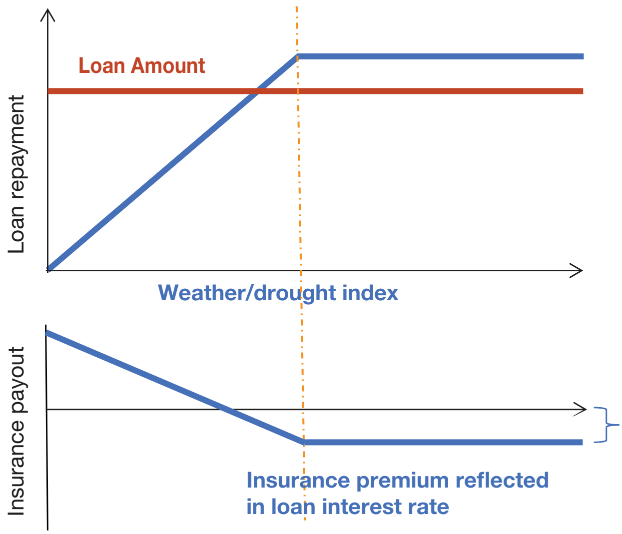


Source: Authors' illustration.

collaboration with our private sector partners Equity Bank Kenya Ltd., Kenya Commercial Bank (KCB), and APA Insurance, along with reinsurance offered by SwissRe. Equity Bank is responsible for farmers' training, loan disbursement, and monitoring in Kenya. KCB does a similar job outside our experimental area. APA Insurance underwrites the weather index insurance embedded in RCC. Figure 12.1 depicts the RCC business model including institutional setup.

Below we provide a brief description of RCC and how it can protect farmers from drought-related production risks. In Figure 12.2, the upper graph shows loan repayment and the lower graph illustrates the underlying insurance payout, which depends on weather conditions (to the left). If the underlying risk (weather-related) worsens and crosses a certain threshold or trigger, the total repayment obligation of the farmer falls linearly, with the difference deposited directly into the farmer's 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, along with the cost of insurance. RCC therefore has 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 underlying weather risk. Over the years we have developed, fine-tuned, and improved the scientific design of RCC (for

FIGURE 12.2 A schematic illustration of risk-contingent credit



Source: Authors' illustration.

details on the evolution of the scientific RCC design, see Shee and Turvey 2012; Shee, Turvey, and You 2019; Turvey, Shee, and Marr 2019).

Our underlying insurance product is weather (rainfall) index insurance that provides protection against rainfall shortage in the long-rain cropping season. The index was constructed based on Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) rainfall measures for the traditional long rain season in Machakos county from October 15 to January 15. The study involved two rounds of loan disbursement among randomly selected smallholder households from Machakos county, with some significant improvements in the insurance component between rounds. During the first round of implementation, from September 2017 to January 2018, historical dekadal (10-daily) rainfall data from 1981 to the present were collected for each of the 11 sub-counties in Machakos county. Seasonal cumulative rainfall measures were fit to a PERT distribution, with a cumulative rainfall "trigger" set at the 20th percentile for each sub-county (Shee, Turvey, and You 2019). A spatially correlated Monte Carlo simulation was used to compute actuarial rates assuming a KSh 300 tick value for every 1 mm of rainfall below the trigger. Although the trigger value and probability distributions differed by sub-county, the actual premiums averaged about 12 percent across districts. With a 25 percent loading factor imposed by the insurer,[3] the yield as a percentage of the loan amount was set at 14 percent for each sub-county, although each of them had a distinct trigger against which indemnities were to be calculated.

At the end of the season, the product suffered significant basis risk in terms of false negatives and intra-seasonal basis risk, warranting some improvements to better capture actual losses experienced by farmers. We modified the insurance component of RCC to better represent the within-season patterning of rainfall. To accomplish this, we re-engineered RCC from a seasonal cumulative rainfall model to a multiple-event model based on 21-day cumulative rainfall, setting the trigger at 50 percent of the historical average rainfall measure over the years and the tick value at KSh 50. We define specific events as 21 fixed days that are overlapping in measurement but non-overlapping in indemnity, implying a multi-event dynamic trigger that can indemnify only once within a period of 21 days (Turvey, Shee, and Marr 2019).[4] Up to four nonoverlapping events, each paying an indemnity, make up the total indemnity.

This structure resolves several problems that have plagued the implementation of rainfall-based index insurance in the past. It directly addresses the problem of intraseasonal drought conditions while providing indemnities to rainfall across phenological growth stages throughout the growing season. Furthermore, it reduces the incidence of type I (receiving an indemnity with no crop loss) and type II (receiving no indemnity, when crop loss occurs) errors. In both instances, we captured loss measure by determining the difference between the actual rainfall and the trigger value by $Max\ (0, Z - R(T))$ where the trigger level is Z and the level of rainfall for the specific period T is $R(T)$. To capture the economic loss, we multiply the above loss measure by a "tick" value, determined in consultation with the participating insurance company. The tick value was determined by the amount required to pay off the loan principal in a worst-case scenario.

Focus group discussions and communication through participatory games

After developing a prototype RCC, we needed local information to decide on different product parameters and to assess feasibility. We first conducted

3 The loading factor is the percentage added above the actuarially fair premium by the insurer to cover their administrative costs and markup.

4 We have also developed a multi-event product that considers crop water requirements/evapotranspiration as the triggering event for rainfall index insurance, a promising product but yet to be empirically evaluated in the field (Ndegwa et al. 2022).

scoping missions in June 2016, holding six focus group discussions (FGDs) in three counties in Kenya—namely, Machakos, Makueni, and Uasin Gishu—to assess farmers' responses and to select our project pilot area. We included diverse counties to assess the suitability of RCC in a variety of agroecologies. The scoping mission aimed to understand the local situation, needs, and the likely reception of RCC. Through qualitative discussions, we collected information on agricultural practices and on historical weather shocks, drought in particular, and the impacts of this on farming households. The FGDs helped us gather information on the timeline and crop growth cycle of maize—the main crop grown in the area—which included sowing time, vegetative growth period (germination to panicle initiation), reproductive growth period (panicle initiation to flowering), ripening period (flowering to mature grain), and harvest time. This detailed information on the maize crop growth cycle helped us incorporate crop phenology to develop and improve RCC. The information on historical drought events reported by the FGD participants also helped the team ground-truth historical remote sensing rainfall indexes. The FGDs also helped us understand farmers' demand for agricultural loans, in which months they need loans, for what purpose, and the best time to repay.

Perhaps the greater challenge lay in communicating the functioning of RCC to farmers who had only basic education. We developed a participatory and pictorial game as an innovative approach to community engagement to communicate RCC to farmers (Shee, Turvey, and Woodard 2015). We assessed the uptake and impact potential of RCC using the game played in a series of FGDs.

The purpose of the participatory role playing game was to convey the design features of RCC and to demonstrate how RCC works and how it can provide

FIGURE 12.3 Participatory RCC games played by farmers in focus groups

Source: Apurba Shee (photographs taken during SATISFy project field visit).

downside risk protection. Farmers selected one option from a set of three pictorially depicted choices with their potential outcomes in good and bad seasons: traditional practice with no need for credit, high-potential practice with traditional credit, and high-potential practice with RCC (a detailed description of the game is presented in Shee, Turvey, and Woodard 2015). Traditional practice referred to agricultural practices where no loan was required; high-potential practice, on the other hand, required a loan (a traditional loan or RCC) for investment in a high-quality improved crop production practice. Participants also were given a realized weather (risk) condition through a random draw of a marker from a bag with one red (represents bad weather) and four green (represents normal weather) markers. In the end, participants calculated the end-of-season earnings according to the realized good and bad weather conditions. Looking at the end-of-the-season earnings for the three choices, farmers realized that they were not subject to negative seasonal earnings with RCC but that, with traditional credit, they had negative earnings in the bad season. Hence, the game showed that, even though farmers earned less with RCC than with traditional credit during a normal season, they were able to be protected in a bad season. Using the participatory role play, farmers were able to see how RCC effectively reduced their downside risk. In the game, about 80 percent of participants opted for high-potential practice with RCC, which revealed strong farmer interest in RCC.

After the scoping mission, the team selected Machakos county for pilot interventions, for two main reasons. First, Machakos is a semiarid and hilly terrain area that receives very low annual rainfall of around 700 mm per year, with average rainfall in the long and short rain seasons being 315 and 266 mm, respectively (Kenya, Ministry of Agriculture, Livestock and Fisheries 2014). Smallholder farmers practice agriculture, with maize the primary staple crop. We therefore expected RCC to be attractive and capable of providing large benefits to the smallholders in the county. Second, our key implementing partner, Equity Bank, has several branches in Machakos county, which could directly facilitate RCC disbursement. Makueni county was also a good fit for the study, but the Bank's presence and coverage were better in Machakos. Uasin Gishu county was not ideal for RCC since drought is not a major production risk there, and hence drought insurance is not a viable intervention.

Behavioral experiment and formative evaluation

Although the qualitative investigation described above generated strong interest in and support for RCC among farmers, the question remained as to whether

FIGURE 12.4 Choice experiment attributes and corresponding levels

Attributes	Levels			
Insurance Cost for borrowing 10,000 KSh loan	500 KSh (5%)	1000 KSh (10%)	2000 KSh (20%)	3000 KSH (30%)
Insurance Payment	Premium added to loan	Pay premium separately		
Insured Risk Covered	High coverage	Medium coverage	Low coverage	
Credit Term	6 months Short	12 months Medium	More than 12 months Long	
Collateral Requirement	No collateral	Partial collateral	Full collateral	
Loan Repayment Flexibililty	Jan . Feb . Mar . Apr Monthly repayment	Jan . Feb . Mar . Apr . May . Jun . Repay at harvest		
Loan Use Flexibility	For any purpose	For agricultural production		
Preferred Season	Short rain	Long rain	Both	
Rainfall Measurement	Shortage for a season	Shortage at crop cycle		

Source: Authors.

RCC could meet their demand and whether financial institutions could supply them. We conducted a formative evaluation through a choice experiment[5] not only to assess the demand and supply feasibility but also to test and adapt the RCC product by incorporating feedback received from supply- and demand-side stakeholders. The detailed choice experiment method is presented in Shee, Turvey, and Marr (2020).

Since RCC is a combination of insurance and credit products, it became a very complex product with many attributes of both. Identifying the preferred attributes of both farmers and financial institutions was central to developing an improved RCC product representing an optimal mix of insurance and credit attributes. Through consultations with stakeholders, the team identified nine attributes for choice experiments: (1) insurance premium; (2) insurance payout;

5 Choice experiments help in eliciting consumer preferences, the theoretical explanation of which is rooted in utility maximization, where individuals derive their utilities from the attributes of a good or service (Lancaster 1966).

(3) insured risk coverage; (4) credit terms; (5) collateral requirement; (6) loan repayment flexibility; (7) loan use flexibility; (8) preferred season for a loan; and (9) rainfall measurement. The first three attributes relate to the insurance component and the remaining ones are associated with the loan component. Figure 12.4 presents the choice experiment attributes and their levels of coverage.

We collected choice data from 330 smallholder farmers and 39 supply-side managers from key insurance companies and banks in Kenya. We analyzed these using the maximum simulated likelihood estimation of a mixed logit model (Train 2009). Demand-side results suggested that farmers preferred credit for both seasons, longer-term credit, no or partial collateral loans, lower risk premiums, high risk coverage, and loans to be used for multiple purposes. Supply-side results suggested that bank and insurance company managers preferred the risk premium to be added with the loan, loan repayment to be done after harvest, credit to be provided for both seasons, loans to be utilized only for agricultural purposes, and loans to be partially or fully collateralized. Hence, we found some conflicts between demand- and supply-side preferences regarding credit term, loan use flexibility, and collateral requirement. While farmers preferred medium- to long-term loans, this was not the case for financial institutions. While farmers preferred loans to be used for multiple purposes, bank managers preferred loans to be used only for agricultural production. While farmers disliked the collateral requirement, bank managers preferred this.

Overall, the choice experiment method of the formative evaluation helped us adapt actuarial RCC design to optimal bundling of attributes by marketing a partial collateral RCC contract, adding insurance premium with loans, and allowing loans to be offered in both seasons with a postharvest repayment schedule. We later piloted this optimal design of the RCC product to smallholder farmers in Machakos county through a full-fledged RCT (presented in the next section).

Apart from the above-mentioned choice experimental evidence of stakeholders' preference on RCC attributes, we conducted a formative evaluation of farmers' demand for RCC, and the socioeconomic factors influencing this. Using baseline household survey data from 1,170 Machakos households during the first phase of RCC implementation (April 2017 to June 2018), we empirically tested factors that could potentially influence the uptake of RCC. In our baseline survey, we adapted and modified the direct elicitation method proposed by Boucher, Guirkinger, and Trivelli (2009) to capture households' credit rationing status; the process is illustrated by Shee, Pervez, and Turvey (2018).

In the baseline survey, a module for eliciting credit rationing status asked the respondents about a set of credit-related experiences and used the responses to classify the credit rationing status of households into the following three groups: (1) unconstrained status, consisting of farmers who were being approached by banks to take credit, who would receive the full credit they requested, or who did not require credit; (2) quantity-rationed, implying financial institutions rationing their credit supply, with farmers either getting less credit than they requested or being denied credit altogether; and (3) risk-rationed, with farmers voluntarily withdrawing themselves from the credit market for fear of losing collateral. Out of the total sample of 1,170, we found 48 percent to be unconstrained, 11 percent to be quantity-rationed, and 41 percent to be risk-rationed. Hence, we found credit rationing to be pervasive in our baseline sample households in Kenya, with about half of the sample credit-rationed in some fashion.

From the first phase of RCC implementation, the average credit uptake rate was 33 percent, with the uptake of RCC significantly higher than that of traditional credit (34 percent and 31 percent, respectively). We then estimated a probit model to identify the factors of credit uptake (uptake = 1, otherwise = 0) (see Ndegwa et al. 2020). We found that quantity rationing had a small positive effect on uptake. This implied that farmers who were quantity rationed were potentially more likely than unconstrained households to take the credit if offered.

However, we also found that risk rationing harmed credit uptake, which implied that risk-rationed farmers were less likely to take the offered credit compared with their unconstrained counterparts. This finding supported the existing theory that, even when provided with agricultural credit, a risk-rationed farmer may still choose to withdraw from the credit market. Risk-rationed farmers do not participate in the credit market because they are afraid of losing collateral or undergoing other defaulting implications.

Among the socioeconomic variables, training attendance, food expenditure, maize labor requirement, hired labor, livestock revenue, and access to credit were found to influence credit uptake positively, whereas nonfood expenditure was negatively related to credit uptake.

Experimental design and impact evaluation

To evaluate the uptake, investment, productivity, and welfare benefits of RCC, we implemented a multi-arm RCT where we compared RCC to traditional credit with no drought insurance attached to it. The RCT design was constructed to provide a statistically valid, representative, and unbiased assessment of the uptake of RCC and its impact on agricultural investment, productivity, and farmer welfare, and to compare it with the effect of traditional credit. In the

RCT, we randomly assigned 1,150 households to one of three research groups: traditional credit (TC) (treatment 1; 350 households), RCC (treatment 2; 350 households), or control (no credit; 350 households). Treatment assignment was carried out in location-level public lotteries: representatives from all the selected households in a location (90 in total) were invited for an initial training on RCC and basic maize agronomic practices, after which they were invited to blindly draw a printed chip from an urn to determine which experimental group they fell in—either RCC, TC, or control.[6] As is common with such RCTs, those who randomly fell into the RCC and TC groups were offered the respective credit types. Credit uptake was not enforced but left to the household's volition.

The evaluation study involved a baseline survey, two phases of project implementation (marketing of RCC and TC loans), and two follow-up surveys. The baseline survey was conducted in May–June 2017 and was followed by the first phase of implementation, when input loans were offered, in October 2017, for the long rain season running from October 2017 to January 2018. The first follow-up (midline) survey was conducted in May–June 2018, roughly eight months from the time the first phase loans had been disbursed. Input loans for the second phase of implementation were offered in October 2019 to be used in the long rain season from October 2019 to January 2020. The end-line survey was planned for May–June 2020 (to maintain consistent timing) but this was disrupted by the COVID-19 pandemic; it was postponed until August–September 2020. Further, whereas baseline and midline surveys were through face-to-face interviews using a long-form structured questionnaire, the end-line survey was conducted via telephone, and the questionnaire itself was revised and significantly reduced so that the interview could be completed within roughly 30 minutes. However, we made extensive efforts to ensure we tracked all key variables needed to complete the study.

Our primary objective in this study was to provide evidence of the efficacy of RCC to engender a transformation and modernization of agriculture in sub-Saharan Africa. To do so, we tested whether RCC and TC yielded ex ante and ex post impacts on agricultural households in our sample area and whether the effects were differential. For ex ante impacts, we considered treatment

6 To confirm that our random assignment to experimental groups was effective, we conducted checks for baseline differences, individually regressing the outcome and control variables against treatment assignments. We started by comparing both treatments to the control group, then compared RCC with TC households. The results indicate that, apart from in the dependency ratio, the control group was not systematically different from the treatment groups. Further, the two treatment arms (RCC and TC) were similar on all outcome and control variables. This suggests that the treatment assignment was balanced and hence selection bias is not a major concern.

effects for on-farm investment in improved maize varieties and chemical fertilizers, as well as the intensity with which these were used. For ex post impacts, we considered household productivity and welfare outcomes.

With considerably high imperfect compliance among the treatment households (credit uptake was 32 percent and 16 percent at midline and end-line, respectively), local average treatment effect (LATE) is the ideal empirical strategy to estimate the impact of RCC and TC on households' outcomes. We estimated LATE by implementing the instrumental variables technique to account for imperfect compliance. We employed the two-stage least squares approach where uptake of either RCC or TC was instrumented by random assignment to either RCC, TC, or control group, respectively.

Ex ante investment impact evaluation results

For indicators of households' agricultural investment, we considered five outcomes: use of fertilizer on maize as a binary choice variable equal to one if chemical fertilizer was used on maize and zero otherwise; chemical fertilizer use intensity proxied by the amount of money (in Kenyan shillings) spent on chemical fertilizers per acre for maize; adoption of improved maize

TABLE 12.1 Results of ex ante impact evaluation

Outcomes	LATE1	LATE2
Panel A: Binary response fertilize use		
RCC	0.135*	0.137
TC	0.132	0.216
RCC=TC: P-value	0.971	0.529
Panel B: Fertilizer spending		
RCC	1,922.156***	1,937.909***
TC	741.569*	969.931**
RCC=TC: P-value	0.004	0.049
Panel C: Improved maize seed use—binary		
RCC	0.069	0.043
TC	–0.044	0.026
RCC=TC: P-value	0.118	0.994
Panel D: Share of land under improved maize seed		
RCC	4.321	1.599
TC	–8.458	–2.045
RCC=TC: P-value	0.089	0.925
Panel E: Area under maize		
RCC	0.237	0.342
TC	0.462	0.291
RCC=TC: P-value	0.572	0.919

Source: Authors.

Note: LATE1 and LATE2 show the LATE estimated with analysis of covariance (ANCOVA) and fixed effects (FE), respectively. ***P<0.01, **P<0.05, *P<0.1.

varieties as a binary choice variable equal to one if improved maize varieties were planted at all and zero otherwise; improved maize adoption intensity measured as the share of maize fields under improved varieties; and area under maize overall. Table 12.1 presents the treatment effect estimates of ex ante investment.

Panel A shows a substantial positive effect of uptake of RCC on the decision to use chemical fertilizer. RCC uptake effects ranged from 13.5 percent to 13.7 percent and were significant in the ANCOVA column. This implies that, compared with others, households that were offered and took RCC were roughly 14 percentage points more likely to use chemical fertilizers on their maize fields. On the other hand, the TC uptake effect ranged between 13.2 percent and 21.6 percent, which, although substantial, was not statistically significant. We could not, however, reject the null hypothesis that the difference between RCC and TC effects (RCC=TC: P-value) was equal to zero. Panel B shows an even higher impact of RCC on fertilizer use intensity where statistical significance was much higher ($p<0.01$) across all models. Uptake of RCC had a substantial and significant effect on maize fertilizer usage whereby those who were offered and took RCC spent roughly KSh 1,900 more on fertilizer per acre than the rest ($p<0.001$). The effects of TC uptake, on the other hand, ranged between KSh 740 and KSh 970, with lower statistical significance. Further, we found strong evidence that RCC effects on maize fertilizer spending were significantly larger than the TC effects (RCC=TC: P-value <0.05).

The LATE effects of TC and RCC on the decision to use improved maize seeds and the intensity of improved maize seed adoption are presented in panels C and D, respectively. Across all the specifications, those who were offered and took RCC were more likely to use improved maize varieties and had a higher share of their maize fields under these. These improvements were, however, marginal and statistically insignificant. On the other hand, those who were offered and took TC appear to have been less likely to use improved maize varieties and had less of a share of their maize fields under these. This negative effect was, however, statistically insignificant. Further, we did not find strong grounds to reject the null hypothesis that RCC and TC effects were statistically not different.

Panel E presents LATE effects on the overall area cultivated with maize. The aim here was to investigate whether RCC and TC had led to the expansion of land cultivated with maize. The estimates were positive but small in magnitude and statistically insignificant. This suggests that both RCC and TC did not lead to any significant change in the area cultivated with maize. We then can conclude that uptake of RCC promoted agricultural intensification but not extensification. We also did not find a significant difference between RCC and TC effects on maize area expansion.

Ex post productivity and welfare impact evaluation results

As for indicators of households' productivity, we considered maize yields and acreage revenue from maize and its main intercrops—common beans and cowpeas. LATE estimates of RCC and TC effects on maize yield and acreage revenue are presented in panels A and B, respectively. We divided the farmer-reported yields by the inverse of the number of reported intercrops to adjust for intercropping in the yield variable. We computed farm revenue by summing the value of acreage production of the three main crops (maize, normal beans, and cowpeas) grown by almost all households in the study area.[7]

For indicators of household welfare, we evaluated the food security situation using the coping strategy index (CSI) and dietary diversity using the household dietary diversity index (HDDI). CSI, as defined by Maxwell and Caldwell (2008), measures the unavailability and insufficiency of food, while HDDI measures the diversity and hence balance of diets. Table 12.2 presents treatment

7 The value of the crops used was the actual market prices of the commodities at Machakos market at the end of each season. We obtained the market prices from the Kenyan Ministry of Agriculture, Livestock, and FIsheries.

TABLE 12.2 Results of ex post impact evaluation

Outcomes	LATE1	LATE2
Panel A: Maize yield		
RCC	–268.911	–116.984
TC	–553.808*	–564.813
RCC=TC: P-value	0.295	0.560
Panel B: Acreage revenue		
RCC	–5,628.192	–5,466.198
TC	–3,644.003	–10,250.567
RCC=TC: P-value	0.678	0.924
Panel C: Food insecurity		
RCC	1.392	2.027
TC	1.350	2.591
RCC=TC: P-value	0.9693	0.7108
Panel D: HDDI		
RCC	–0.165	–0.283
TC	–0.226	–0.288
RCC=TC: P-value	0.855	0.619

Note: LATE1 and LATE2 show the LATE estimated with ANCOVA and FE, respectively. ***P<0.01, **P<0.05, *P<0.1.

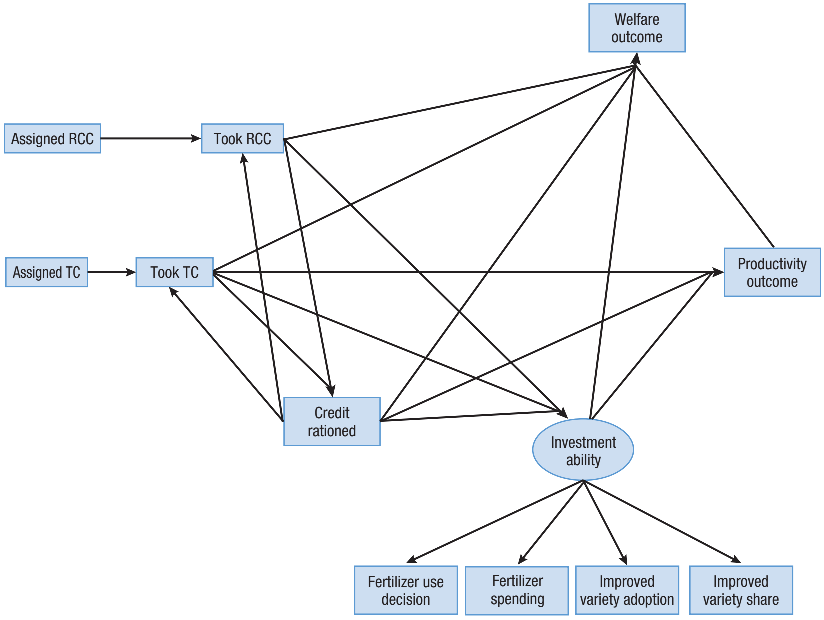
effect estimates of ex post investment. To calculate the CSI, we selected the eight most common food insecurity coping strategies and asked respondents the number of days in the past seven they may have employed each. Our scale ranges from 0 to 56, or simply the product of the maximum possible number of days (7) and coping strategies (8). The higher the score, the more times a household had to employ one of the coping strategies, and hence the worse off they were regarding food insecurity. To construct the HDDI, we asked respondents if in the past 7 days they had consumed a whole host of food items, categorized into 15 discrete food groups. We then created binary response variables corresponding with the 15 food groups, whose values were 1 if at least 1 food item in the group was consumed at least once in the past 7 days, and 0 otherwise. We then summed up the food groups for each household, which gave us their score on a 15-point scale. The higher the score, the more diverse the diet; hence, positive effects were desired. LATE effects on CSI and HDDI are presented in panels C and D, respectively.

The results in Table 12.2 indicate that uptake of both RCC and TC did not lead directly to any significant improvement in the ex post outcomes (both productivity and welfare) of interest. However, we use the structural equation modelling (SEM)[8] approach to assess if such benefits of RCC and TC could be reached but via intermediary outcomes. Figure 12.5 presents the hypothesized impact pathways between the treatments, the intermediate, and the main outcomes. Here, we consider maize yield and overall acreage revenue as our productivity indicators, and CSI as our welfare indicator. As such, we have three main SEM models, one for each outcome. We consider credit rationing and investment ability as the intermediate factors between credit uptake and households' productivity. Both variables (credit rationing and investment ability) are further considered as mediating for welfare, where one of the productivity indicators (revenue) is included as an additional mediator between credit uptake and households' welfare. Table 12.3 presents the results of the three SEM models. Each model bears the title (as indicated in the column heading) of the main productivity or welfare outcome whose impact pathways are being assessed. A model comprises simultaneous regression equations; in the table, the outcome for each individual equation is bolded while the predictors are indented.

First, all three models exhibit average fitted uptake of RCC and TC (27.6 percent and 23.3 percent, respectively) across the two intervention implementation phases. Further, credit-rationed status did not significantly or

8 See Heckert, Olney, and Ruel (2019) for a recent and closely comparable application of SEM in impact and mediation analysis.

FIGURE 12.5 **Structural equation model showing the causal pathways from treatments (RCC and TC) to the intermediate and main (productivity and welfare) outcomes**



Source: Authors.

substantially affect the uptake of the credit offered, whether RCC or TC. This eliminates reverse causality and simultaneity concerns when credit rationing is used as an intermediary variable for other impact outcomes. Across all models, uptake of either RCC or TC had a desirable and statistically significant effect on the main intermediate variables, namely credit rationing and investment ability. Both RCC and TC reduced credit rationing while increasing investment ability. The effect of credit rationing on investment ability, although negative across all the models, was small in size and statistically insignificant, implying that credit rationing did not significantly moderate the impact of RCC or TC on households' investment ability.

Looking at the productivity rows under the yield model column, the direct paths from credit uptake (either RCC or TC) were positive but statistically insignificant. Also, credit rationing had a negative and significant effect on maize yield while investment ability had a positive and significant effect on maize yield. These results suggest that the impact of RCC and TC on maize yield is fully mediated by credit rationing and investment ability. Results

TABLE 12.3 Results of structural equation models for yield, revenue, and food insecurity

	Yield model		Revenue model		Food insecurity (CSI) model	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Uptake of RCC						
Assigned RCC	0.276***	0.009	0.276***	0.009	0.276***	0.009
Credit-rationed	–0.003	0.016	–0.003	0.016	–0.003	0.016
Uptake of TC						
Assigned TC	0.233***	0.009	0.233***	0.009	0.233***	0.009
Credit-rationed	0.01	0.017	0.01	0.017	0.01	0.017
Credit rationing						
Took RCC	–0.17**	0.081	–0.17**	0.081	–0.17**	0.081
Took TC	–0.278***	0.097	–0.278***	0.097	–0.278***	0.097
Investment ability						
Took RCC	0.13***	0.025	0.13***	0.025	0.13***	0.025
Took TC	0.121***	0.027	0.12***	0.027	0.121***	0.027
Credit-rationed	–0.009	0.012	–0.009	0.012	–0.009	0.012
Productivity outcome						
Took RCC	209.1	183.212	297.17	3245.433	287.387	3245.499
Took TC	243.558	217.09	7523.47**	3867.181	7512.314**	3867.151
Credit-rationed	–149.485***	42.668	–3227.554***	757.191	–3227.587***	757.097
Investment ability	535.75***	66.885	7243.822***	1188.38	7236.618***	1187.758
Welfare outcome - CSI						
Took RCC					–0.386	0.441
Took TC					–0.635	0.479
Credit-rationed					1.491***	0.209
Investment ability					–0.788**	0.348
Revenue					–0.001***	0.000

Note: ***$P<0.01$, **$P<0.05$. All coefficients are unstandardized. SE = standard error. In bold are lefthand variables and indented are righthand variables for each equation.

indicate that the negative effect that credit rationing has on maize yields can be abated with expanded access to credit. Similarly, the positive effects that investment ability has on maize yields can be augmented further through enhanced access to credit. The case is similar with revenue, where acreage revenue declines with credit rationing and increases with investment ability, and the two intermediates can be enhanced with credit access, which will eventually lead to better farm revenues. The only difference here is that, although the impact of RCC uptake on-farm revenue is fully mediated by credit rationing and investment ability (a positive but insignificant coefficient), that of TC uptake is partially mediated by the same variables. It is possible that there could be other mediation routes between credit uptake and farm revenue that are not included in this analysis. Finally, looking at the welfare outcome rows under the food insecurity column, we see that the uptake effect of both RCC and TC on the food insecurity index (CSI) is fully mediated by credit rationing, investment ability, and household productivity, which in this model is proxied by acreage revenue. Food insecurity reduces with an increase in investment ability and farm revenue and increases with credit rationing.

Scaling potential

Outside of our experimental design, we conducted commercial implementation of RCC in Kenya, where any farmers interested in RCC can apply for RCC loans from respective local banks (KCB). The outcome of our scientific approach to RCC implementation through RCT, plus the commercial application, has provided strong grounds for extending RCC to many countries in Africa. There is considerable potential for scaling up within and beyond semiarid areas of Kenya as many countries in sub-Saharan Africa often face severe agricultural risks (resulting from extreme weather conditions such as droughts and floods) and insufficient access to credit. Our study area, Machakos county, is characterized by a semiarid climate that is shared by many sub-Saharan African countries, especially those in the Horn of Africa, but also including many Sahelian countries and several southern African countries like Botswana, Mozambique, Namibia, South Africa, and Zimbabwe. In addition to similarities in climate and agricultural risks faced, farmers in other contexts also find themselves quantity- or risk-constrained in their access to credit, thereby limiting their ability to invest in modern agricultural inputs that could help them escape pernicious poverty traps.

We foresee the following scale-up opportunities for RCC:

Innovation on enhancing uptake: Because credit is interlinked with agricultural production risks, loan default risk will also be reduced significantly. RCC also eliminates the drawbacks of stand-alone index insurance products by not requiring farmers to pay a premium upfront. This mechanism of RCC eliminates farmers' liquidity constraint (which is considered the main barrier to insurance uptake) and could enhance RCC uptake significantly.

Reducing basis risk: We developed multi-event index insurance and RCC products to incorporate intraseasonal variations and integrated crop water needs to further improve the triggering mechanism. We also plan to use satellite-derived soil moisture and vegetation data along with rainfall measurements to develop a composite weather index to efficiently capture the risk associated with extreme weather situations. This will reduce the design-related basis risk significantly and increase the value proposition of the product.

Scalable index and RCC design: At the heart of designing RCC, the objective of an index is mapping a signal (for example, weather or remotely sensed data) to an index that can predict crop yield accurately. We have developed a spatial econometric framework that allows maximum information extraction in the presence of missing data for investigating the construction and design of scalable RCC indexes.

Developing methodology for less data-intensive RCC development: Currently, the data requirements for the design of RCC are quite high. For the RCC to be commercially scalable, we plan to develop design tools directly from biophysical variables that can be modeled for wider applications. Although in this model it could be difficult to conceptualize basis risk, this will be advantageous for scaling-up, particularly for the areas where household survey data on crop production are not available.

Efforts to reduce the transaction cost of RCC delivery: Developing a mechanism that is relatively cheap but reliable is important for reducing the transaction costs of RCC delivery. In this regard, we plan to use a mobile-based application to create cost-effective information dissemination and trust in RCC products. Also, since our local implementers already have local branches, village banking agents, and distribution channels, we can create a robust and efficient delivery mechanism for RCC.

Effective financial education and extension: Along with local partners, we put special effort into financial education and extension with farmers. We plan to enhance our strategic partnerships to expand financial education and awareness.

Synergies with government and complementary interventions: Our project objectives are in line with the Kenya Rural Development Program's goal of managing drought and food security. RCC can also build synergy with sustainable intensification interventions by responding to farmers' investment needs.

Commercial viability and welfare impact: We believe RCC structures could provide the proper incentives not only to entice banks (for example, Equity Bank) to increase the supply of credit but also to attract farmers to the credit market. We understand that long-run commercial sustainability will depend on the effective assessment of the social and economic benefits of RCC. Our impact evaluation results justify the long-term effect of RCC.

Conclusion

Over the past two decades, index insurance has gained some global success in managing weather risks faced by farmers but has been hampered by low demand. New insurance approaches are needed that bundle index insurance with term credit to reduce the downside risk facing farmers and the default risk facing lenders. The upfront premium required for standard insurance imposes significant liquidity constraints on poor farmers and also transfers income across time. RCC can overcome this by removing the liquidity constraint, reducing the effects of climate risk, and increasing the uptake of agricultural insurance via better targeting of poor farmers. Since insurance can substitute (at least partly) for collateral, the RCC mechanism has the potential to encourage otherwise risk-rationed farmers to take up RCC loans. Since the indemnity from the embedded insurance is applied to the underlying debt obligation, RCC can reduce the probability of default and build trust that can boost uptake. However, literature on the benefits of insurance bundled with credit remains very thin, especially evidence based on field experiments.

This chapter has discussed the development, testing, and adaptation of RCC through innovative pre-experimental methods, along with impact evaluation through implementing a full-fledged randomized experiment. After developing a prototype of scientific bundling of insurance with credit, we incorporated feedback from the community and stakeholders and incrementally co-developed the full RCC product, and subsequently implemented it in Kenya.

Through formative evaluation, we found that linking insurance to credit improved the uptake of agricultural credit. This confirms that downside risk is a hindrance to credit uptake, limiting the already liquidity-constrained farmers' options with regard to raising the capital needed to enhance their productivity and welfare. Our impact evaluation results indicate that access to credit, regardless of the type, can improve farmers' agricultural investment, which helps transform their livelihoods and quality of life. Further, RCC effects were consistently higher than TC effects, and the difference was statistically significant in the adoption of chemical fertilizers, a key investment indicator. These additional benefits, coupled with enhanced uptake, suggest that RCC could be an effective way to promote both credit and insurance uptake, which in return can lead to enhanced household productivity and welfare.

Our findings suggest that developing policies that hedge smallholders against systemic shocks, such as drought, is one way of enhancing access to credit. The use of formal insurance markets is a viable policy since it transfers the risk outside the household and hence protects its collateral. Bundling insurance with credit also minimizes the risk of default by smallholder borrowers, which lessens financial risks to lenders that threaten their business stability—a common phenomenon when rural agricultural production systems experience systemic shocks such as drought. Financial institutions keen on growing their agricultural lending portfolio may then consider insurance-linked products to offer cheaper and safer loans to farmers. However, insurance and credit providers should ensure greater transparency for farmers by providing continuous index updates using a simplified pictorial tool. In this regard, digital technology such as mobile phones could be effective. In a situation where climate change is expected to put unprecedented strains on smallholder agricultural systems, RCC can not only help increase the resilience of the food system but also improve smallholders' productivity and growth outcomes.

Although we scientifically designed RCC as a product that can reduce intertemporal basis risk by incorporating crop phenology in the insurance pricing framework, lack of reliable historical crop yield data has been a hindrance to the creation of an improved insurance mechanism that can reduce basis risk significantly. Ideally, estimating and predicting yield using weather indexes would be preferrable. This is common in low-income economies. We therefore recommend governments promote large-scale data collection and make such data available for researchers. In this regard, big data and machine learning techniques could improve index construction by inducing improved model specifications and predictions of expected crop yield. Further research in this area is warranted, particularly on trying alternative indexes, building composite indexes, or developing multiple crop and/or whole-farm index insurance and insurance-linked products.

Productivity, welfare, and resilience outcomes are higher-level benefits that may be harder to achieve and to estimate by means of the limited periods in an experiment. Also, this study may have limited predictive power because of the low uptake of credit offered. As such, although we made every effort to control for any form of endogeneity, we cautiously interpret and claim causality and recommend that the impact results and interpretations be treated as indicative. We hope this motivates further investigation, especially with longer panels, a variety of credit and insurance products, and higher uptake.

Further, financial literacy remains very low among smallholder farmers in low- and middle-income country settings. Although financial education through Equity Bank was part of the RCC protocol, we recommend investigation of the ideal education and extension methods to train farmers on such products, ensuring that key details are covered while maintaining a level of simplicity congruent with low literacy and numeracy among rural smallholders in the region. In this regard, providing financial education using simplified games through extension services at the county level could be an effective government policy.

Finally, as the recent literature suggests, women are important agricultural producers, especially in sub-Saharan Africa, but face greater credit constraints than men. It is, therefore, worth exploring how to include more women farmers in the RCC program, and how this would improve women's access to credit and empowerment in society.

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