JAE Journal of Agricultural Economics

Journal of Agricultural Economics
doi: 10.1111/1477-9552.12401

Heterogeneous Demand and Supply for an Insurance-linked Credit Product in Kenya: A Stated Choice Experiment Approach

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(Original submitted June 2019, revision received July 2020, accepted August 2020.)

Abstract

We employ a discrete choice experiment to elicit demand and supply side preferences for insurance-linked credit, a promising market-based tool for managing agricultural weather risks and providing access to credit for farmers. We estimate preference heterogeneity using primary data from smallholder farmers and managers of lenders/insurers combined with household socio-economic survey data in Kenya. We analyse the choice data using maximum simulated likelihood and Hierarchical Bayes estimation of a mixed logit model. Although there are some similarities, we find that there is conflicting demand and supply side preferences for credit terms, collateral requirements, and loan use flexibility. We also analyse willingness to buy and willingness to offer for farmers and suppliers, respectively, for the risk premium for different attributes and their levels. Identifying the preferred attributes and levels for both farmers and financial institutions can guide optimal packaging of insurance and credit providing market participation and adoption motivation for insurance-bundled credit product.

Keywords: *Bayesian estimation*; *choice experiment*; *insurance-linked credit*; *Kenya*; *maximum simulated likelihood*; *random parameter logit*; *willingness to pay*.

JEL classifications: *Q14, Q11, Q18*.

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1. Introduction

Uninsured agricultural risk and limited access to credit are important issues in agricultural development and are considered among the sources of poverty traps in sub-Saharan Africa (Barrett *et al*., 2006; Barrett and Carter, 2013; Santos and Barrett, 2019). Agricultural production is affected by drought-related climate risks which are increasing in frequency and severity in the region (Daryanto *et al*., 2016; Lesk *et al*., 2016). Agricultural productivity is also affected by limited access to capital that inhibits smallholder farmers' ability to purchase and optimise agricultural inputs. The impacts of drought-related climate risks are particularly acute in Kenya. According to the Government of Kenya, four consecutive years (2008–2011) of drought amounted to US$12.1 billion in losses, including losses in assets and from disruptions in the economic flow across all sectors (GOK, 2014). Government and donor communities alone cannot finance severe shocks such as these, and efforts are underway to secure market-oriented private sector interventions. A promising intervention, and one which forms the backdrop to this paper, is insurance-bundled credit product which links insurance directly to agricultural credit to protect both borrower and lender against specified contingent risks (Skees and Barnett, 2006; Skees *et al*., 2007; Giné and Yang, 2009; Carter *et al*., 2011; Collier *et al*., 2011; Miranda and Gonzalez-Vega, 2011; Shee and Turvey, 2012; Farrin and Miranda, 2015; Shee *et al*., 2015; Carter *et al*., 2016).

While theoretically appealing, little is known about the preferred attributes of insurance-linked credit products. To scale up insurance-linked credit products, their attributes become important determinants not only in defining utility-maximising choices but also in the design and marketing of the underlying insurance attributes and how these relate to credit demand. Understanding preferences for and implicit prices of the different attributes of insurance-linked credit products can provide useful policy information for practitioners and decision-makers in the market. Equally important are the supply-side attributes and the preferences placed on linked-credit by bankers and insurers. Indeed, the prevailing literature on the lender-borrower relationship shows that, in many respects, there is a gap in expectations and understanding between demand and supply factors. Thus, heterogeneous choice in bundled-credit exists not only within borrower and lender groups but also between them. In other words, a supply-demand equilibrium in an insurance-linked credit market requires not only alignment in the costs of credit and insurance, but also the specific attributes of credit, including the nature and type of insurance, the term of credit, and collateral requirements. We address this equilibrium specifically by investigating the willingness-to-pay (WTP) and willingness-to-offer (WTO) from identical in-the-field choice experiments applied to both borrowers (smallholder farmers) and financial providers (lenders and insurers) in the drought-prone Machakos County in Kenya.

A problem in understanding credit demand is that empirical measurements from survey data in the short run are unresponsive to interest rate changes since, by and large, most farmers receive the same interest rate or a range of rates over a small interval. The statistical results might then indicate that demand is highly inelastic (the variance in loan amounts exceeds the variance in interest rates). Likewise, it is difficult to infer the effective credit supply by the finance providers. Consequently, economists and practitioners have turned to randomised control and other experimental methods, though these studies are rather limited.[1] Even rarer are singular studies that use in-the-field experimental techniques to examine both demand and supply stakeholders at the same time, using the same instrument. Recent studies have estimated farmers' preferences and willingness to pay for particular attributes of insurance (Fraser, 1992; Wang *et al*., 1998; Akter *et al*., 2009, 2016; Hill *et al*., 2013; Liesivaara and Myyrä, 2014; Gallenstein *et al*., 2019), and choice experiments have found broad application in estimating consumer preferences in the non-insurance literature (e.g. Lusk *et al*., 2003, 2006; Basu and Hicks, 2008; Ortega *et al*., 2012; Ward *et al*., 2014, 2016; Ward and Makhija, 2018). However, none have investigated preference heterogeneity in both demand and supply side of an insurance-linked credit product as we do here. We use stated preference discrete choice experiments in the field to analyse how farmers and finance providers respond to different attributes and levels for insurance-linked credit. Since observational data with any variation in the contractual design of insurance-linked credit are not available, we exploit the choice experiment approach to elicit preferences for product attributes that are difficult to observe in the market.

Our field choice experiments with attributes of a risk-contingent credit (RCC) product was first piloted with farmers in a randomised control trial (RCT) in the Machakos County of Kenya in the long rain season of 2017/2018.[2] Our choice experiment was implemented independently of the RCT, but our 330 demand respondents were randomly selected from the initial 1,170 Kenyan farmers included in the RCT. On the supply side, we also met concurrently with 39 supply-side stakeholders drawn from commercial banks and insurers. This sample was drawn from agricultural lenders at the local bank and insurance companies that offered RCC to farmers for the RCT. In addition, we met with agricultural lenders from competing banks and MFIs in and around Nairobi, as well as villages and townships throughout the Machakos County. The implementing details are provided below, but it is important to emphasise that with this experimental design we can investigate heterogeneous choice amongst both borrowers and lenders/stakeholders over the same set of attributes – an experimental protocol that we have yet to find elsewhere in the literature.

The lender-borrower relationship is fraught with multiple tensions. The greater tension is the demand-driven willingness to pay (WTP, cost minimisation) and the supply-driven willingness to offer (WTO, profit maximisation) a loan product. But in terms of risk mitigation, there are also economic tensions in collateral requirements, insurance coverage, and cost of insurance. Our approach of offering identical experimental choices to both demand and supply-side stakeholders allows us to distinguish the weighting that each place on different attributes. The extent of heterogeneity among the farmers and financial institutions may have implications for implementation strategy and policy because it implies that individuals will not respond uniformly to economic incentives.

The next section provides a brief review of the literature and study background of risk-contingent credit. Section 3 describes the design of our discrete choice experiment and the econometric framework for estimating demand and supply-side preferences

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[1]See, for example, Turvey *et al*. (2012), Banerjee and Duflo (2014), Karlan *et al*. (2014), Banerjee *et al*. (2015), Bogan *et al*. (2015), Cao *et al*. (2016).

[2]The specifics of the RCT, its outcomes and impacts, are to be presented in follow-on papers that are being prepared contemporaneously.

and heterogeneity in these preferences for RCC. Our primary data and results of empirical analysis including interpretations are presented in section 4. Section 5 concludes with some economic implications.

2. Bundling Insurance with Credit – Literature and Study Background

Over the past two decades, index-insurance has gained some success around the world for managing agricultural risks faced by farmers, but is mostly hampered by low demand (for recent reviews, see Miranda and Farrin, 2012; Marr *et al*., 2016; Cole and Xiong, 2017; Jensen and Barrett, 2017; and the critique by Binswanger-Mkhize, 2012). Attention among economists and practitioners has now turned to new approaches to the bundling of index insurance with smallholder agricultural credit, to manage drought-related climate risk faced by farmers and reduce default risk faced by lenders. Unlike traditional credit products, insurance-linked credit facilitates risk management by including hedging protection into loan payment obligations. When a weather index such as rainfall level worsens and crosses a predetermined trigger, the insurance pays out thus reducing the farmers' repayment burden. With the removal of critical liquidity constraints, combined with the inter-temporal transfer of climate risk, bundling insurance with credit mechanism can achieve better targeting of poorer farmers, increase economic efficiency, provide climate resilience, reduce income inequality, and eliminate weather-based poverty traps.

Consequently, there has been an emerging literature on insurance-linked credit in developing countries. Giné and Yang (2009) investigated the adoption of an operating loan in Malawi, where the payoff was determined by rainfall, and found low take-up. Karlan *et al*. (2011) investigated the adoption of price-contingent credit in Ghana and found a limited uptake. Carter *et al*. (2011) examined the impacts of RCC on financial market deepening and its impacts on farm households, concluding that RCC capitalised the adoption of new technology. Shee and Turvey (2012) showed how risk-contingent instruments can be priced in practice and, using simulated field data, they concluded that an imbedded price option for pulse crops in India provided downside risk protection for pulse farmers. Shee *et al*. (2015) conducted a field-based feasibility of RCC with Kenyan pastoralists and dairy farmers. Casaburi and Willis (2018) implemented insurance-linked contract farming and found a 72% take-up rate. These papers investigate bundled products where agricultural risks are linked to loans directly made to farmers or agribusiness. Miranda and Gonzalez-Vega (2011) and Collier *et al*. (2011) provide conceptual frameworks in which financial institutions themselves link their loan portfolios to El Niño risks in Central America. In addition to our own RCT, other implementation projects on bundled credit can be found in the agricultural insurance scheme in India where weather-based crop insurance is bundled with agricultural loans taken from commercial banks and the Planet Guarantee project in Burkina Faso where index insurance is bundled with credit for maize and cotton farmers.

In a typical market for credit, the demand for agricultural credit is not necessarily a direct demand, but an indirect demand derived from the demand for inputs (Shee and Turvey, 2012). The derived demand for credit is dependent upon the liquidity available to the farm household in terms of savings and the liquidity provided by accessing credit (Barry *et al*., 1981). This derived demand and the demand for liquidity above savings and ready cash may influence farmers' willingness to pay an interest rate premium. However, increased use of debt comes with an increased probability of default. The lender's response to this risk is to impose collateral requirements (Barry *et al*., 1981;

Binswanger and Sillers, 1983; Bester, 1985; Bhattacharyya, 2005; Shee and Turvey, 2012). Bester (1985) has argued that higher interest rates can substitute for collateral. The relationship between interest rates and collateral is important for understanding the demand for credit. Mathematically, the inverse relationship between interest rates and collateral assumes that they are substitutes. However, in reality, this may not be correct. Increasing evidence of risk rationing behaviour (Boucher *et al*., 2008, 2009; Verteramo-Chiu *et al*., 2014) can be quite significant and adds a complicating dimension to the problem that significant numbers of farmers will reduce borrowing, or not borrow at all if production (or consumption) assets are put at risk.

The introduction of insurance with credit can affect both the supply and demand for credit. Karlan *et al*. (2014) find that relaxing credit constraints without mitigating uninsured risk is not effective for agricultural development. On the supply side, the presence of insurance against agricultural perils should encourage supply, shifting the supply curve outwards with more loan offerings at lower interest rates. Likewise, in the presence of insurance, and with insurance being a substitute for collateral, demand should also be encouraged. The effect of insured credit might also reduce lender incentives to impose harsh collateral requirements (Shee and Turvey, 2012) and other forms of non-price rationing that will then induce risk-rationed farmers to enter the credit market and encourage greater borrowing from non-risk-rationed farmers. This is consistent with a crucial argument in Boucher *et al*. (2008) that the presence of insurance should eliminate risk-rationing behaviour.

Our study is based on an existing project that implements RCC with Kenyan smallholder farmers to manage their drought-related climate risk and to provide them with access to credit. In the fall of 2017, our research group piloted RCC for the first time in Machakos County in Kenya, with loan indemnities linked to long and short rains. The implementation design was a randomised control experiment including no-loan, traditional loan, and risk contingent credit, with a sub-experiment, also randomised, on RCC premium subsidisation. Uptake of offered traditional and RCC loans was about 40%. In time, our group will evaluate the impact on agricultural productivity, household income, consumption smoothing, savings and investment, household nutrition, and so on, using traditional credit versus RCC against the no-credit counterfactual.

Figure S1 shows our study area in Machakos consisting of five sub-counties in Machakos where RCC operation is ongoing in 13 locations. This is a semi-arid and hilly terrain area that receives a 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 (GOK, 2014). It has experienced severe rainfall deficit (major drought) about every decade and slight to moderate rainfall deficits (minor droughts) once every 3–4 years (GOK, 2014). Due to this semi-arid climate, smallholder farmers' main food crop is maize.

3. Empirical Methodology

We use stated preference discrete choice experiments (CE) to estimate demand and supply-side preferences for different components of an insurance-linked credit product. The theoretical underpinning of CE is rooted in the Lancastrian approach to utility where individuals derive their utilities from a good through each of its attributes (Lancaster, 1966). In our context, the good is the insurance-linked credit product, which can be viewed as a collection of attributes such as cost and coverage of risk, credit term, collateral requirement, and loan repayment flexibility. To understand preferences for and implicit prices of different attributes, it is appropriate to view the demand and supply decisions as components of a utility maximisation problem, where the utility is maximised by choosing a combination of attributes among a set of feasible alternatives (McFadden, 1974). To econometrically estimate marginal preferences for the various attributes we design a discrete CE and collect data characterising participants' choices and their attributes.

Adamowicz *et al*. (1998), Carlsson and Martinsson (2001), and Lusk and Schroeder (2004) have documented the advantages of using stated CE over revealed preference methods and found no statistically significant difference between results from both the approaches. Since the objective of this paper is to estimate marginal values for various attributes of bundled credit products from both demand and supply sides with common attributes affecting non-monetary choices, we use a stated CE approach.

3.1. Design of our discrete choice experiment

Framing of choice experiments is critical. Our experiments were designed after years of study in Kenya discussing the ideas behind RCC with farmers and related stakeholders, including our implementation partners. These efforts have been documented in Shee *et al*. (2015), Shee *et al*. (2019) and Turvey *et al*. (2019). Furthermore, we initiated an RCT involving 1,170 farmers in Machakos County in 2017, with implementation continuing in 2019 in Machakos, and a non-RCT commercial trial being implemented by a second Kenyan bank in a neighbouring county. Our sample of 330 farmers was randomly drawn from the initial RCT participants in Machakos, for which we had data from the 2017 baseline survey. Thus, in terms of framing the experiment, not only was our research team well versed in credit conditions in Machakos, but also the participants were aware of, and some actually experienced RCC (Shee *et al*., 2019). Likewise, on the supply side, our team had been meeting with stakeholders regularly since 2016. Our stakeholder participants on the credit supply side were drawn from organisation staff from lenders and insurers in the area. These stakeholders were either familiar with our efforts or directly involved in implementation. As might be expected in the course of running in-field experiments, the aggregate numbers of supply-side stakeholders from which to draw were limited. Ultimately, we drew 39 supply-side respondents from a small (but unknown) pool.

The attributes and their levels selected for the CE were based on our interactions with farmers and stakeholders in the field as outlined above, including farmers' opinion in focus group discussions, meetings with bank and insurance company managers, consulting the scientific design team, and baseline survey results. Through this process we identified nine attributes for our choice experiment: (1) insurance cost; (2) insurance payment; (3) insured risk coverage; (4) credit term; (5) collateral requirement; (6) loan repayment flexibility; (7) loan use flexibility; (8) preferred season for a loan; and (9) rainfall measurement. A summary of the choice experiment attributes, and their corresponding levels is presented in Table 1.

Given that the product is a bundled credit product, the attributes were designed to capture both the insurance and the credit aspects. The first three attributes relate to the insurance part which derives the willingness to pay for traditional insurance attributes, including the cost of the RCC, the coverage level with respect to the underlying rainfall risk, and how the insurance was to be paid. On this latter point, there was some discussion amongst stakeholders as to whether farmers should pay for the insurance separately from the credit, or whether the insurance cost should be added to the

Table 1
Choice experiment attributes and corresponding levels

Attributes	Levels
Insurance cost for borrowing 10,000 KSH loan	500 KSH (5%); 1,000 KSH (10%); 2,000 KSH (20%); 3,000 KSH (30%)
Insurance payment	Premium added to the loan; Pay premium separately
Insured risk coverage	Low coverage (covering rare risk, 1 in 20 years); Medium coverage (covering medium risk, 1 in 10 years); High coverage (covering frequent risk, 1 in 4 years)
Credit term (length of loan)	Short (up to 6 months, e.g. until harvest); Medium (6 months to 1 year); Long (more than 1 year)
Collateral requirements	No collateral required; Partial collateral required; Full collateral required
Flexibility in loan repayment	Make monthly repayments; Repay at time of harvest only
Flexibility in loan use	The loan can be used for any purpose; Loan can only be used in agricultural production
Preferred season for loan	Long rain; Short rain; Both
Rainfall measurement based on	Total rainfall shortage for a season; Rainfall shortage measured at various stages of the crop growth cycle (vegetative, reproductive, and ripening stages)

credit, with interest being paid on the whole. The base interest rate of 14% was used in credit calculations for all farmers whether they were selected under the RCT for standard credit or for RCC. Thus, the critical aspect at the margin is the premium cost. We ranged the premium cost from 5% to 30%. The actuarial rate was 13% but there were additional insurance loading costs (25%) and administrative charges. The effective insurance premium was approximately 17% with all costs accounted for. In our RCT, a subset of 100 farmers was randomly selected to receive a subsidy ranging from 25% to 100% of the insurance premium. Those results showed that the demand was in fact highly inelastic for RCC. The premium attribute provides a basis to determine whether the demand for RCC faces an inelastic or more elastic demand. In our RCT, we measured risk in terms of cumulative rainfall within a season, and the risk coverage offered was approximately 1 in 5 years. However, in the insurance design, there was much debate as to whether the insurance should cover more frequent events at a higher cost, or rarer events at significantly lower costs. The insured risk coverage attribute covers the range of risk discussed with stakeholders. Also, in the design process, there was discussion as to whether the risk should be based on long rains, short rains, or both (ultimately the RCT made loans only for the long rains). That's why we included 'preferred season for loan' as an attribute in the CE. We also discussed how rainfall should be measured. The options included measuring risk according to the cumulative rainfall measure within the season, against a rainfall distribution approach which has been proposed by some scholars.[3]

[3]Ultimately the RCT in 2017 used the cumulative rainfall measure as described in Shee *et al.* (2019), but the 2019 implementation is based on a multiple event, phenological approach as described in Turvey *et al.* (2019).

The remaining attributes capture characteristics associated with the loan. Shee and Turvey (2012) hypothesised RCC as a pathway towards collateral-free loans as proposed in Bester (1985). In reality, however, while credit risk is most aligned with failures in the long and short rains, there is still significant exposure to other risks including pests, disease, flooding, and moral hazard (e.g. voluntary default). So, in practice, RCC could never be collateral-free. From our baseline survey, we determined that 42% of farmers were risk rationed (Shee *et al.*, 2019), suggesting that collateral requirements could be a great barrier to loan demand, even if the most significant risk was protected. The collateral attribute was designed to capture this effect. There were also questions on how the loan could be used. If the loans were to be used for purposes other than agricultural production, repayment would have to come from sources other than agriculture. However, in focus groups, farmers indicated a significant demand for credit for other uses. Finally, loan repayment was considered either on a monthly basis or after harvest. This latter option was encouraged by the findings of Weber and Mußhoff (2013) who explored 'flex loans' (repaid after harvest) in Madagascar. This is also consistent with the principle of liquidity matching. Ultimately our RCT restricted credit use to agricultural use by issuing vouchers to local Machakos suppliers, with a 'flex' repayment schedule.

3.1.1. D-optimal choice set design

To construct the choice sets, we specified the D-Optimality criterion using a modified Federov search algorithm, based on calculating the determinant of the variance-covariance matrix of the parameters from a non-linear logit model. Choice sets were constructed with three alternatives available for respondents. We did not include an opt-out alternative in the choice sets.[4] Our choice set design consisted of 54 unique choice sets, which were assigned to 6 different blocks, such that each respondent was required to respond to 9 choice sets with unique levels of attributes. The D-efficiency

[4]The literature is mixed on whether an opt-out option should be included. Excluding an opt-out option has some advantages and disadvantages. In our instance, we had strong *a priori* evidence that all participants had a demand for RCC, was more than a hypothetical and was contained within their choice set. This is quite different than the use of opt-out (for example, Basu and Hicks, 2008) in a fair-trade coffee experiment in which it is unknown if the opt-out is due to particular attributes or whether the cohort simply did not like coffee. Ready *et al.* (2010) argued that the opt-out provides a means to determine the likelihood of purchase as well as estimates of marginal WTP, whereas excluding an opt-out provides only estimates of marginal WTP. Veldwijk *et al.* (2014) pointed out that including an opt-out option may automatically imply reduced effectiveness as there would be more answering categories. Veldwijk *et al.* (2014) empirically tested the effect of including an opt-out option in discrete choice experiments on participants' choice behaviour and found that respondents' education level and the location of the opt-out option made a very small difference in behaviour between with and without opt-out choice models. On balance, our decision to exclude an opt-out was predicated on the observation that our farmers had already indicated their demand for RCC relative to the status quo, so the likelihood of opting out due to no demand was very small. By the same token, excluding the opt-out in the supplier experiment was warranted, since, at the time of the experiment, the lender/insurers suppliers had already committed to supplying. Ultimately, the motivation of our choice experiment was to estimate the demand and supply side preferences for specific attributes of an RCC product. Including an opt-out option in these circumstances complicates the choice for our participants, and risks not learning anything for our specific purposes, since it would not provide any insight into attribute-level tradeoffs.

of our choice set design was approximately 96%. However, to achieve the efficiencies in choice experiments, consideration needs to be given to sample size. For the main effect logit model, we estimate the number of parameters we needed to estimate was: $No\ of\ Parameter = No\ of\ Levels - No\ of\ Attributes + 1$, where $No\ of\ Levels = \sum_{i=1}^{A} L_i, A$ is the number of attributes, and L_i is the number of levels of attribute i.

Based on the experimental design we needed at least 24 − 9 + 1 = 16 parameters to estimate. However, consideration of two interaction effects increased the number of parameters required for efficient estimation. As proposed by Orme (1998), Johnson and Orme (2003) and Rose and Bliemer (2013), a common rule of thumb for an estimate of the sample size required for a main effect choice experiment should be $N \geq 500\left(\frac{l^*}{S*J}\right)$, where S is the number of choice tasks presented to each respondent (9, in our case), J is the number of alternatives per choice task (3 in our case), and l^* is the largest number of levels of any of the attributes (4, for insurance cost). The values of S and J can be determined exogenously but should satisfy the rank condition, $S(J - 1) > K$, where K is the number of parameters to be estimated. Estimating only the main effects can lower the values for S and J, but this precludes any consideration of correlated or heterogeneous preferences. To satisfy the rank condition we elected a protocol with three alternatives per choice set, and with each respondent responding to nine choice sets. We also considered two-factor interaction effects in addition to the main effects which satisfied rank condition. As a consequence, we need at least 75 individuals in our sample. Given the nature of the block design, our sample included 330 farmers and 39 lender stakeholders. These 39 supply-side stakeholders fall short of the 75 required for efficient estimation. As previously discussed, we are unsure if the actual number of professionals in the Machakos region even approaches 75 members. Even though the sample size for insurance and credit providers was low (because there are only a finite number of managers to choose from) our D-optimal choice set design should provide reliable parameter estimates at a smaller sample size (Yu *et al.*, 2009; Bliemer and Rose, 2010).

To ensure data reliability, we placed special emphasis on increasing farmers' understanding of and involvement in tasks. Thus, we included pictorial illustrations of the product attributes and their levels in the choice cards to facilitate respondents' choice tasks (see an example of a choice card presented to participants in Figure S2). To reduce the response burden and fatigue on the participating households we grouped the choices sets into six groups of nine choice sets each. The households were then randomly assigned to the choice sets presented in one of the six groups, with an equal proportion of households allocated to each of the groups. Since we have nine attributes, a full profile design may lead to cognitive burden and response fatigue. To overcome this problem, we use partial profile designs (e.g. Kessels *et al.*, 2014) allowing only five variables to vary on any one card. Nonetheless, we observed no evidence of response fatigue but observed quite the opposite with many farmers eagerly engaged and willing to talk about their farming operations with our surveyors.

3.1.2. Sampling and data collection

Figure 1 shows a schematic summary of the sampling design. A total of 1,170 households were randomly selected from 13 locations in 5 sub-counties of Machakos in April–June 2017 and a baseline household survey was conducted simultaneously. The sample households were provided with two phases of training: financial literacy

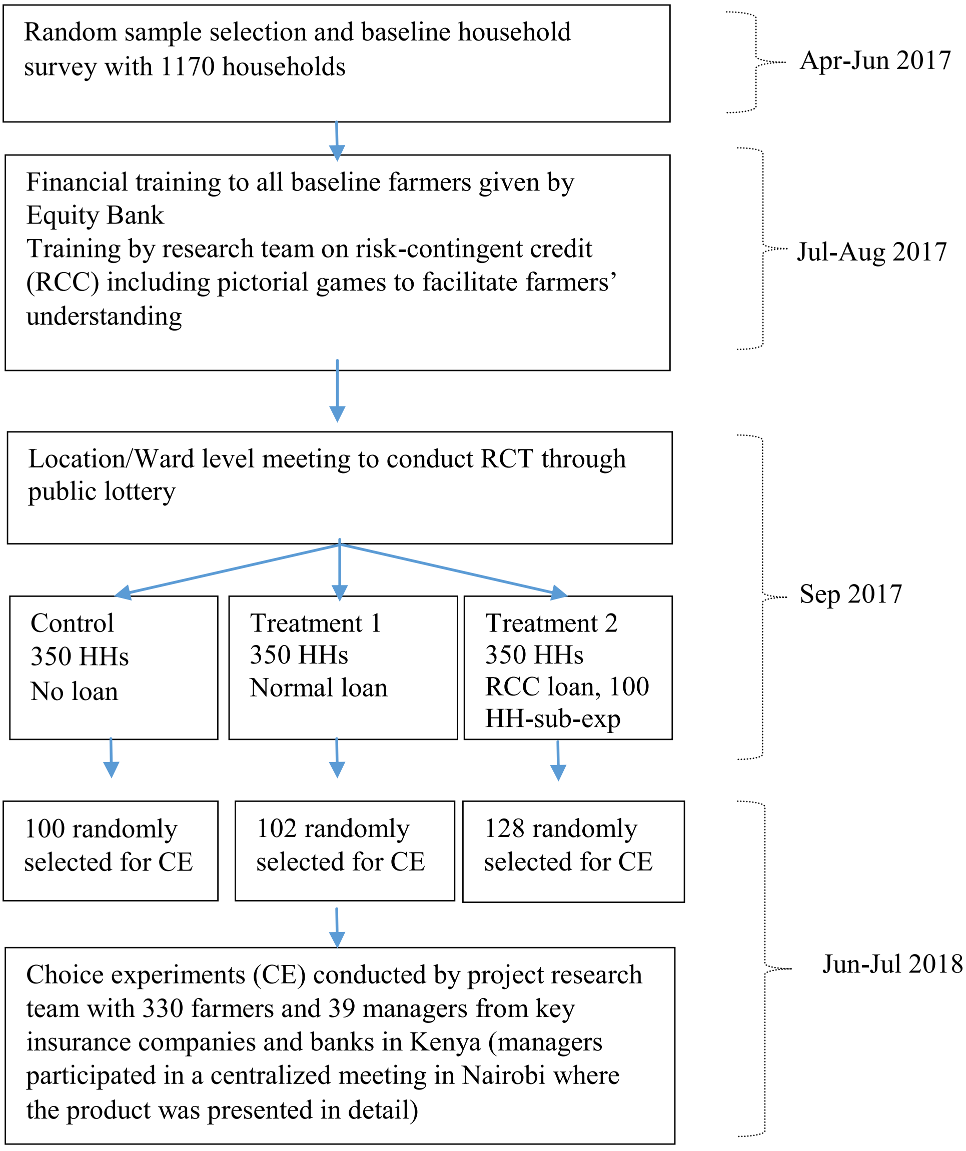

Figure 1. Experimental design

training by Equity Bank and risk-contingent credit training by the research team. After the training, a public lottery was conducted at each location to randomly divide the sample households into three groups: traditional credit (treatment 1; 350 households), RCC (treatment 2; 350 households), or control (no credit; 350 households). An additional 100 households were part of a sub-experiment for RCC demand estimation. After these lotteries, farmers were given 2 weeks to decide whether to apply for a loan. In October 2017 the first loan disbursements were completed by Equity Bank. For the period of September 2017 to May 2018, the households were monitored for loan repayment. As part of the RCC contract improvement and scaling up effort, the research team conducted the choice experiments reported in this paper in June and

July 2018 with 330 farm households (randomly selected from all three RCT groups) and 39 managers from key insurance companies and banks in Kenya. All farmers were members of the RCT and were familiar with RCC. Participating managers were drawn from two sources: the first source was a centralised meeting in Nairobi where RCC product was presented in detail by team leaders. The second group was opportunistically drawn, with team leaders visiting bank and insurance offices in townships in areas in which the choice experiments were being held.

3.2. *Econometric framework*

Since the data from stated preference CEs are discrete choice decisions, they can be analysed within a random utility framework (McFadden, 1974). Suppose that individual n faces J alternatives contained in a choice set (t). We define an underlying latent variable u_{nj} that denotes the indirect utility associated with individual n choosing alternative $j \in J$. Random utility maximisation implies that individual n will choose alternative i if and only if $u_{ni} > u_{nj} \forall j \neq i$. Following standard practice, we assume that indirect utility is linear and can be written as:

$$u_{njt} = x'_{njt}\beta_n + \varepsilon_{njt} \tag{1}$$

where x'_{njt} is a vector of attributes for the j th alternative, β is a vector of preference parameters, and ε_{njt} is a stochastic component of utility that is independently and identically distributed across individuals and alternatives. Assuming that ε_{nj} follows a Gumbel (extreme value type I) distribution, the probability that individual n will choose alternative i from among J alternatives can be obtained from a conditional or multinomial logit model:

$$P_{nit} = \frac{\exp(x'_{nit}\beta)}{\sum_{j=1}^{J} \exp(x'_{njt}\beta)} \tag{2}$$

which can be estimated using maximum likelihood. However, a drawback of the multinomial logit model is its imposition of a proportionate substitution pattern (also called independence from irrelevant alternatives or IIA) and its inability to handle random test variations. To overcome these limitations the literature suggests a generalised random parameter logit model or the mixed logit model. An advantage of the mixed logit model is that it is highly flexible and can approximate any random utility model. This overcomes the limitations of multinomial logit by allowing random test variation and observing substitution patterns from the data (McFadden and Train, 2000). In our context, since the random drawing of smallholder farmers was designed to avoid uniformity and homogeneity, their 'demand' preferences for RCC attributes may also be heterogeneous. As previously discussed, a random drawing of a subset of managers from financial institutions would have been fruitless since the sample was so small. Our approach was to get as broad a representation as possible. Since our representative sample was heterogeneous by design – lender versus insurers, urban versus rural – their 'supply' preferences for RCC attributes are also likely to be heterogeneous. If the 'demand' and 'supply' samples show greater uniformity and homogeneity in their respective preferences, then the mixed logit model converges to the same solution as the conditional logit model.

Within the discrete choice literature, the preference heterogeneity can be estimated through several approaches such as maximum simulated likelihood and Bayesian methods to estimating the mixed logit model. This discussion draws heavily from Train and Sonnier (2005), Hole (2007) and Train (2009). The researcher specifies a distribution for β_n, $f(\beta|\theta)$ where θ are the parameters of the distribution which has a mean vector, b, and covariance matrix S, $\beta_n \sim N(b, S)$. The unconditional probability of the observed sequence of choices is the conditional probability integrated over the distribution of β, can be written as the following:

$$P_n(\theta) = \int \prod_t \frac{\exp(x'_{nit}\beta_n)}{\sum_{j=1}^{J} \exp(x'_{njt}\beta_n)} f(\beta|\theta) d\beta \tag{3}$$

The integral in (3) does not have a closed-form solution and the above probability (also called mixed logit probability) can be estimated using maximum simulated likelihood approach, where we can approximate the probability by drawing from the density $f(\beta|\theta)$. Following Train (2009) the steps are as follows: (1) we take a draw of β_n from $f(\beta|\theta)$; (2) we calculate the conditional logit probability; and (3) we repeat this calculation many times and average over the results. Finally, the simulated log-likelihood (SLL) is calculated by summing the log of simulated probabilities over all individuals and the estimates of b and S are calculated by maximising the SLL (Train, 2009).

Another approach of estimating the individual level heterogeneity is the use of the Hierarchical Bayes estimation procedure to the mixed logit model (Bayesian mixed logit). Bayesian procedures overcome two prominent difficulties associated with classical procedures: (1) the Bayesian procedure does not require maximisation of a likelihood function which may at times fail to converge; and (2) more desirable estimation properties, such as consistency and efficiency can be attained under more relaxed conditions (Train, 2009). Following Train (2009) the prior beliefs about b and S are specified as $b \sim N(0, v)$, v is large, and $S \sim IG(v, 1)$ for $\text{v} \to 1$, where IG stands for inverted Gamma distribution. The parameters b and S are called population-level parameters. Following Train (2009) we use Gibbs sampling to estimate three sets of parameters b, S, and $\beta_n \forall n$. The posterior for b, S, and $\beta_n \forall n$ is:

$$K(b, S, \beta_n | Y) \propto \prod_n \frac{\exp(x'_{ni}\beta_n)}{\sum_{j=1}^{J} \exp(x'_{nj}\beta_n)} \phi(\beta_n | b, S) k(b, S) \tag{4}$$

Draws from this posterior are obtained through conditional posteriors using Gibbs sampling. The steps are as follows: (1) we take a draw of b conditional on values of S and β_n, (2) we take a draw of S conditional on values of b and β_n, and (3) we take a draw of β_n conditional on values of b and S. Finally, these steps are repeated for many iterations. In step 3, since we do not know the shape of the conditional posterior, the Metropolis-Hastings algorithm is used to draw from distribution. In steps 1 and 2, Gibbs sampling is used to draw from these posteriors. Gibbs sampling for this model is fast and efficient because there are no layers that require numerical integration. In fact, the first layer utilises a product of logit formulas for a given value of β_n. Steps 1 and 2 do not utilise the data at all, because they depend only on the draws of β_n.

The parameter estimates from both the maximum simulated likelihood and Bayesian approaches to estimating mixed logit models provide little economic information given the non-cardinal nature of utility. We use the estimated parameters to obtain willingness to pay (WTP) measures. WTP is calculated as the change in price or premium in order to keep the same level of utility after an attribute (nominal) changes. WTP for the kth attribute can be written as follows:

$$WTP_k = -\frac{2\beta_k}{\beta_p} \tag{6}$$

where β_k is the estimated parameter of the kth attribute, and β_p is the estimated coefficient of price or premium in our context. Following Lusk *et al*. (2003) the WTP measure is harmlessly multiplied by two due to our use of effects coding. Being the ratio of two distributions the attribute WTP may be undefined or may not be amenable to interpretation. In our estimation of the mixed logit model, we specify the premium coefficient to be fixed (homogeneous across observations) and allow the coefficients of other attributes to vary normally, a common assumption in many mixed logit applications (Hole, 2007; Ward *et al*., 2014). The specification of the fixed premium coefficient allows the distribution of the attribute WTP to be the same as the distribution of the random attribute coefficient, with mean and variance scaled by the fixed premium coefficient providing a meaningful interpretation (Revelt and Train, 1998; Ward *et al*., 2014).

4. Data and Results

The interviewed households in the choice experiment took part in a long household survey a year before the choice experiment. The household survey was conducted through computer-assisted personal interviewing (CAPI) under a multi-year impact evaluation of RCC. Although the project impact evaluation plan is not germane to this study, we used the household survey data to obtain socio-economic data of the households. The sample for the household survey was randomly selected from 13 locations in 5 sub-counties (Matungulu, Kangundo, Kathiani, Mwala, Yatta). In each location, 6 villages were randomly selected and ultimately 15 households from a list of families in a village were selected. The household survey collected information on various socioeconomic variables such as demography, agricultural land characteristics, production and inputs, livestock ownership, and credit. The household survey data were collected from 1,170 households, all of them received training on RCC in September 2017. The choice experiment data was collected from 330 households randomly selected from these 1,170 households as explained in Figure 1. Table S1 shows the locational distribution of our CE households.

Key socio-economic variables from the CE sample (330) are provided in Table 2, as well as households that received any loan through the project. Compared to households with no loan, households who received a loan the previous year exhibited higher maize yield and crop revenue per acre,[5] and a higher number of working-age labourers in the household but the lower percentage of households that are headed by a

[5]We calculate crop revenue per acre using three main crops grown in the area (maize, beans and cowpeas). We take the average market prices for those three crops in Machakos area (the average price per kilogram of maize, beans and cowpeas were 43 Ksh, 90 Ksh and 109 Ksh, respectively) and combine these with crop production and crop area data to calculate crop revenue per acre.

Table 2
Socio-economic characteristics of sample households

Household (HH) characteristics	HH received loan	HH with no loan	Total
Yield of maize (kg/acre)	317.61***	224.52***	245.78
Crop revenue (KES/acre)	11,185.07*	9,214.70*	9,664.68
Household size	5.47	5.42	5.43
Female headed household	0.17**	0.23**	0.21
Age of the head	55.79	56.71	56.5
Max years of education in the household	11.24	11.03	11.08
No. of working age labour	3.43**	3.20**	3.26
Total land size (acre)	3.98	4.02	4.01
Tropical livestock units: total	4.12	11.55	9.85
Distance from the HH to the closest plot	1.07	1.05	1.06
Average travel time to seed supplier (minutes and one way)	29.46	30.75	30.45

*Significant at 10% indicate difference in means between sub-samples.
**Significant at 5% indicate difference in means between sub-samples.
***Significant at 1% indicate difference in means between sub-samples.

female. We use some of these variables as interaction terms in the estimation of our choice models.

The choice data were collected from 330 farmers and 39 managers from key insurance companies and banks in Kenya. Farmers were randomly assigned to a block of choice sets and shown each choice set in that block, one set at a time. The 39 supply-side financial institution participants represented both urban (20) and rural (19) branches covering 22 managers from banks and 17 managers from insurance companies. Because each manager had to choose from nine different choice cards with three alternatives to choose from in each card, the total number of rows was 39 * 9 * 3 or 1,053. Respondents' household ID, random block number and the choice indicator for the choice they made for each choice set were recorded. All responses were collected using CAPI. We treat the premium of insurance as a continuous variable in the regression. This reduces the number of parameters needed to be estimated and allows for the calculation of willingness to pay.

Table 3 presents estimation results from the maximum simulated likelihood of mixed logit model (presented in equation 4), without interaction terms, for both demand and supply sides.[6] The significance of standard deviation coefficients shows

[6]The mixed logit models are estimated in Stata using the mixlogit command (Hole, 2007). Although we report only the mixed logit results, we also estimated the conditional logit model, presented in equation (2) and found almost similar mean parameter estimates. In addition, at the request of the reviewer and the editor, we estimated the mixed logit model in WTP space. In Table S2 in the Appendix S1, we provide the demand side estimation results in WTP space and found the results to be very similar to the results presented in Table 3. WTP space estimation in the supply side, however, did not converge.

Table 3
Maximum simulated likelihood of mixed logit without interaction

Variables	Demand side		Supply side	
	Estimate	Std error	Estimate	Std error
Mean coefficient				
Insurance payment [Pay premium separately]	−0.21***	0.08	−1.29***	0.34
Insured risk coverage [High coverage]	0.22***	0.08	0.27	0.36
Insured risk coverage [Low coverage]	−0.03	0.09	−0.56	0.29
Credit term [Long]	1.07***	0.10	−1.06***	0.31
Credit term [Medium]	0.92***	0.10	−0.11	0.25
Collateral requirement [Full collateral]	−0.50***	0.11	−0.19	0.37
Collateral requirement [No collateral]	0.38***	0.09	−0.84***	0.35
Loan repayment flexibility [Monthly repayment]	−0.51***	0.12	−0.53*	0.33
Loan use flexibility [For agricultural production]	−0.46***	0.10	0.99***	0.29
Preferred season [Both]	1.22***	0.10	0.92***	0.30
Preferred season [Long rain]	0.66***	0.10	0.33	0.32
Rainfall measurement [Shortage at stages of crop growth]	0.23***	0.08	0.56*	0.32
Premium	−0.00***	0.00	0.00	0.00
Standard deviation coefficient				
Insurance payment [Pay premium separately]	0.55***	0.15	0.77	0.49
Insured risk coverage [High coverage]	0.03	0.32	1.27***	0.40
Insured risk coverage [Low coverage]	0.41**	0.19	0.31	0.96
Credit term [Long]	0.39**	0.20	0.19	0.64
Credit term [Medium]	0.45***	0.17	0.33	0.53
Collateral requirement [Full collateral]	0.84***	0.14	1.47***	0.42
Collateral requirement [No collateral]	0.75***	0.12	0.82*	0.47
Loan repayment flexibility [Monthly repayment]	1.58***	0.14	1.28***	0.48
Loan use flexibility [For agricultural production]	1.16***	0.13	0.50	0.45
Preferred season [Both]	0.65***	0.13	0.96**	0.40
Preferred season [Long rain]	0.48***	0.17	0.71	0.59
Rainfall measurement [Shortage at stages of crop growth]	0.50***	0.16	1.30***	0.44
Number of Halton draws	500		500	
Simulated log-likelihood	−2,732.19		−317.78	
LR chi^2	251.78		35.71	
Number of rows	8,694		1,053	

that there is significant preference heterogeneity for most of the attributes, confirmed by the likelihood ratio test for the joint significance of the standard deviations (Table 3), which justifies the use of a mixed logit model. For the demand side, except for insured risk coverage (low coverage), all other parameters are statistically significant with expected signs. Although the coefficient for premium is very low, it is negative, meaning farmers are price sensitive and prefer a lower premium price, holding other attributes constant, but the preferences are highly inelastic. Farmers have high negative preferences for full collateral over partial collateral, and they mostly prefer no collateral, as might be expected. In terms of loan repayment, farmers prefer to repay after harvest, with a strong negative preference for repaying the loan monthly. Farmers prefer to use the loan for any purpose rather than using only for agricultural production. They also prefer to receive the credit in both long and short rain seasons and their preferred term of credit is long or medium term.

On the other hand, the 'supply' side preferences for some attributes are different, as one would expect. The premium does not seem to be a relevant attribute for managers of financial institutions. Managers do not seem to prefer zero collateral at all, and they prefer short-term credit over long- and medium-term credit. Managers strongly prefer loans to be used only for agricultural production purposes. These results suggest that there are conflicting demand- and supply-side preferences for credit term, collateral requirement and loan use flexibility. These are expected in any lender-borrower relationship. Lenders will prefer a shorter-term loan to reduce loan default while farmers prefer longer terms to smooth liquidity; lenders require collateral to secure the loan, while farmers (particularly those that are risk rationed, see Ndegwa *et al.*, 2020) are less willing to put collateral at risk; and lenders would prefer a loan for specific uses that provide a return to capital, while farmers prefer greater fungibility in loan purpose. Loans offered in both long and short seasons are preferred for both demand- and supply-side stakeholders.

Table 4 presents estimation results from the maximum simulated likelihood of a mixed logit model with interaction terms, for both demand and supply sides. Similar to the findings from Table 3, we see that the preferences for demand and supply sides are congruent for an insurance payment option, loan repayment flexibility, and preferred season whereas they are conflicting for credit terms and loan use flexibility. We notice that farmers who received loans in the previous season prefer the loan to be used only for agricultural production purposes, aligned with suppliers' preferences. Female farmers prefer monthly loan repayment compared to male farmers although an average farmer and a supplier do not prefer loans to be repaid monthly. Compared to managers from insurance companies, bank managers do not prefer credit disbursement in both seasons. It is also evident that managers from banks have more negative preferences compared to their insurance company counterparts on making loans without any collateral. Clearly, there is some heterogeneity about the preference for RCC attributes among male and female-headed households. Similarly, we notice some heterogeneity among insurance and bank company managers on their preference for RCC attributes.

The results of Hierarchical Bayes estimation of the mixed logit model represented by equation (4) are reported in Table S3. For analysing choice experiments in agricultural economics, Hierarchical Bayes estimation is rarely used. For both demand and supply sides, we report posterior means, posterior standard deviations and subject-level standard deviations. The standard deviation of the posterior distribution in Bayesian estimation is analogous to the standard error in the frequentist concept and, accordingly, the level of significance was determined. The posterior mean values represent marginal utility parameters that provide relative values associated with each attribute level. On the demand side, the Bayesian estimates of all attributes are similar to the results obtained in Table 4, except the insurance payment which has now become insignificant. On the supply side, the Bayesian estimation results are similar to the results obtained in Table 4, except the credit term and collateral requirements

Table 4
Maximum simulated likelihood of mixed logit with interaction terms

	Demand side		Supply side	
Variables	Estimate	Std error	Estimate	Std error
Mean coefficient				
Insurance payment [Pay premium separately]	−0.24**	0.10	−1.09***	0.49
Insured risk coverage [High coverage]	0.29***	0.10	−0.01	0.63
Insured risk coverage [Low coverage]	−0.07	0.11	−0.24	0.43
Credit term [Long]	1.18***	0.13	−0.46	0.43
Credit term [Medium]	1.00***	0.13	0.10	0.41
Collateral requirement [Full collateral]	−0.52***	0.13	−0.27	0.61
Collateral requirement [No collateral]	0.39***	0.11	0.41	0.40
Loan repayment flexibility [Monthly repayment]	−0.70***	0.14	−1.34***	0.53
Loan use flexibility [For agricultural production]	−0.56***	0.13	1.24***	0.46
Preferred season [Both]	1.11***	0.12	1.72***	0.48
Preferred season [Long rain]	0.69***	0.13	−0.11	0.58
Rainfall measurement [Shortage at stages of crop growth]	0.21**	0.10	0.26	0.64
Premium	−0.00***	0.00	0.00	0.00
loan category [Loan] * Loan use flexibility [For agricultural production]	0.49**	0.22		
loan category [Loan] * Preferred season [Both]	0.37*	0.21		
hh_female [1] * Collateral requirement [No collateral]	0.57**	0.25		
hh_female [1] * Loan repayment flexibility [Monthly repayment]	1.35***	0.34		
Institution type [Bank] * Collateral requirement [No collateral]			−2.04***	0.58
Institution type [Bank] * Preferred season [Both]			−1.11**	0.57
Standard deviation coefficient				
Insurance payment [Pay premium separately]	0.52***	0.15	0.98***	0.51
Insured risk coverage [High coverage]	0.08	0.29	1.31***	0.39
Insured risk coverage [Low coverage]	0.33	0.24	0.06	1.16
Credit term [Long]	0.43**	0.17	0.22	0.46
Credit term [Medium]	0.49***	0.15	0.03	0.49
Collateral requirement [Full collateral]	0.85***	0.14	1.39***	0.41
Collateral requirement [No collateral]	0.72***	0.13	0.18	0.59
Loan repayment flexibility [Monthly repayment]	1.49***	0.14	1.20***	0.45
Loan use flexibility [For agricultural production]	1.13***	0.13	0.18	0.56
Preferred season [Both]	0.63***	0.13	0.20	0.46
Preferred season [Long rain]	0.51***	0.16	0.70***	0.28
Rainfall measurement [Shortage at stages of crop growth]	0.47***	0.18	1.56***	0.46
Number of Halton draws	500		500	
Simulated log-likelihood	−2,707.37		−300.92	
LR chi^2	234.28		35.83	
Number of rows	8,694		1,053	

Notes: The interaction terms are specified to be fixed in the mixed logit estimation. Among the interaction terms, only the terms with significant coefficients are presented in the table.

Table 5
Mean willingness to pay and willingness to offer estimates for RCC attributes

		Demand side (KSH)			Supply side (KSH)		
Factor	Feature setting	WTP	LL	UL	WTO	LL	UL
Insurance payment	Pay premium separately	−885.3	−1,645.3	−125.3	−2,787.9	−19,842.0	14,266.2
Insured risk coverage	High coverage	1,049.8	254.1	1,845.5	−35.2	−3,180.9	3,110.5
Insured risk coverage	Low coverage	−248.5	−1,031.0	534.0	−605.6	−4,811.7	3,600.6
Credit term	Long	4,338.0	2,899.2	5,776.7	−1,184.4	−8,725.4	6,356.6
Credit term	Medium	3,663.2	2,344.7	4,981.6	261.9	−2,304.1	2,827.8
Collateral requirement	Full collateral	−1,909.8	−2,941.8	−877.8	−684.3	−5,858.5	4,489.9
Collateral requirement	No collateral	1,429.5	551.6	2,307.4	1,062.4	−5,746.0	7,870.7
Loan repayment flexibility	Monthly repayment	−2,571.3	−3,811.8	−1,330.9	−3,432.2	−24,481.2	17,616.8
Loan use flexibility	For agricultural production	−2,036.7	−3,098.7	−974.8	3,180.3	−16,334.4	22,694.9
Preferred season	Both	4,051.7	2,649.8	5,453.6	4,420.6	−22,721.5	31,562.8
Preferred season	Long rain	2,531.2	1,385.3	3,677.2	−289.6	−3,616.5	3,037.4
Rainfall measurement	Shortage at stages of growth	766.7	2.0	1,531.5	677.4	−4,502.0	5,856.9

Notes: 95% confidence intervals (lower limit (LL) and upper limit (UL) are calculated using the Krinsky Robb method (Hole, 2007).

which have now become significant. The estimates of the interaction terms provide similar results – male farmers strongly dislike monthly repayment compared to female farmers. Interestingly, farmers who received loans in 2017 prefer loans to be repaid monthly compared to farmers who did not receive loans in 2017.[7] Compared to insurance companies, banks do not like offering loans in both seasons. In terms of no-collateral loans, banks have more negative preferences compared to insurance companies.

We estimate the mean willingness to pay (WTP) along with their 95% confidence intervals derived from the maximum simulated likelihood estimates of a mixed logit model with interaction terms for both demand and supply sides. To keep the consumer just as well off, a trade-off between increasing one discrete attribute from 0 to 1 and increasing the price (premium), gives the WTP for that attribute. Table 5 summarises the calculated WTP and WTO for changes in particular attributes of the RCC product. The numeraire in the insurance premium is measured in Kenyan shillings (KSH).

For example, an average farmer is willing to pay 885 KSH less for a premium to be paid separately compared to adding the premium with loans. Similarly, a finance provider would be willing to value 2,787 KSH less for the option of paying the premium separately compared to adding the premium with a loan option although confidential limits indicate the mean WTO estimate is not significantly different from zero. Farmers' WTP decreases by 2,036 KSH if loans can be used only for agricultural purposes compared to loans to be used for any purpose, whereas finance providers' WTO increases by 3,180 KSH if loans are used only for agricultural production, although according to the confidence limits the mean estimate is not significantly different from zero. From Table 5, we see that WTP-WTO (credit demand and credit supply) are conflicting for credit terms and loan use flexibility whereas WTP-WTO is congruent for an insurance payment option, loan repayment flexibility, and preferred season. The table also shows on demand side the WTP for farmers increases if RCC is available for both seasons compared to long or short rain season. The mean WTO from supply side also increases on average if RCC is available for both seasons although the confidential limits indicate the mean WTO estimate is not significantly different from zero. This finding is consistent with the historical drought occurrence that happened almost evenly in both seasons. It is also indicative of credit demand in both seasons.

5. Concluding Comments

Efforts to address weather-related risks and limited access to credit in smallholder agriculture have resulted in the promotion of index insurance-linked credit products in developing countries. Although bundling insurance with credit is a win-win proposition, questions remain as to whether the attributes of this innovative bundled product can meet the demand for smallholder farmers and whether financial institutions

[7]In the 2017 RCT one third of farmers were offered traditional loans, one third offered risk-contingent credit loans, and one third – used as a control – were not offered a loan at all. Whether a traditional or RCC loan was offered, or no loan offered was randomly determined by drawing a chit from an urn. About 63% of farmers offered either loan type, did not accept the loan. Our random draw of participants for the choice experiment described in this paper was independent of 2017 loan status.

will be willing to offer them, and also about the optimal packaging of insurance and credit components that will meet the preferences of both demand and supply sides.

We use a discrete choice experiment to examine demand and supply-side preferences for attributes of insurance-linked credit in Kenya, and model heterogeneity in these preferences using primary data from smallholder farmers and managers of financial institutions combined with household socio-economic survey data. We analyse the choice data using maximum simulated likelihood and Hierarchical Bayes estimation of the mixed logit model. Our research provides a novel approach of comparing demand and supply-side preferences to examine gaps in expectations from both sides of a potential risk-contingent credit market.

We find that farmers prefer credit for both seasons (long and short rains), credit terms to be one year or longer, no or partial collateral for loan, lower risk premium, high insured risk coverage, and loans to be used for any purpose. Supply-side results suggest that managers of financial institutions prefer the risk premium to be added with the loan amount, loans to be repaid after harvest, credit available for both seasons, loans to be used only for agricultural purpose, and bank managers preferred loans to be fully or partially collateralised. Overall, there are conflicting demand and supply-side preferences for credit term, loan use flexibility, and collateral requirement. While long-term loans are preferred by farmers, they are not preferred by finance providers. Farmers prefer medium-term credit over short-term credit although suppliers do not prefer either. Farmers prefer loans to be used for any purpose, but the managers tend to prefer loans to be used only for agricultural production purposes, as an investment in productive activities is perceived to enhance the probability of loan repayment. No-collateral loans are preferred by farmers whereas they are not preferred by bank managers.

We also analyse willingness to pay (WTP) and willingness to offer (WTO) for farmers and suppliers, respectively. WTP-WTO levels are most conflicting between demand and supply sides for credit term and loan use flexibility whereas WTP-WTO are congruent for an insurance payment option, loan repayment flexibility and preferred season. In terms of collateral requirement, farmers' WTP increases whereas bank managers' WTO decreases if the credit is collateral-free compared to a full collateral loan. Since the WTP-WTO for partial collateral increases for both farmers and bank managers, our results suggest development of a partial collateral contract for risk-contingent credit.

If risk-contingent credit is to be scaled up, our recommendation is to develop and market a partial collateral RCC contract, insurance premium to be added with loans, loans to be repaid after harvest, and loans to be offered in both long- and short-rain seasons. Identifying the preferred attributes and levels for both farmers and financial institutions can guide the optimal packaging of insurance and credit providing market participation and adoption motivation for insurance-bundled credit products. Our findings can complement actuarial design and ratemaking.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supplementary Material. On-Line Appendix.

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