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Rural Credit, Food Security, and Resilience

An Empirical Evaluation from Kenya

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Notices

Abstract

In this paper, we examine the role of credit in enhancing rural households' food security and resilience. In so doing, we consider resilience as a higher order capacity outcome, different from traditional development outcomes associated with households' or individuals' welfare. We evaluate the effectiveness of two types of agricultural production credit products, one a traditional credit and one that is linked to rainfall index insurance to protect borrowers against the adverse effects of drought. Based on a randomized controlled trial conducted in Machakos county, Kenya, we report both intent-to-treat effects as well as local average treatment effects to demonstrate the impacts of these credit products not only among borrowers, but the broader effects of expanding rural credit markets. We see generally low levels of food security resilience among our sampled households, but we find compelling evidence that credit and expanded credit markets more broadly had beneficial impacts on enhancing households' food security and resilience. Despite the differences in the two credit products being evaluated, we do not find an appreciable difference in the effects of the two credit types, concluding that the expansion of affordable agricultural credit markets should be among the key policy tools for building resilience among rural smallholders.

Keywords: Credit, insurance, food security, resilience, smallholders

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1 Introduction

Agricultural credit plays a vital role in helping households overcome liquidity constraints and enhancing productivity and well-being (IFAD, 2016). Access to credit enables smallholder farmers to invest in productivity-enhancing inputs and technologies such as high-quality seeds, chemical fertilizers, irrigation systems, pesticides, and other essential inputs that are critical for improving crop yields and reducing vulnerability to environmental shocks. Additionally, credit can facilitate investment in post-harvest infrastructure, such as storage facilities, which help minimize losses and extend the shelf-life of produce. By improving productivity and reducing post-harvest losses, agricultural credit directly contributes to increasing the availability and stability of food supplies at the household level, thereby enhancing food security and leading to improved welfare among the rural households. Moreover, credit can empower farmers to diversify their income sources, reducing their dependency on a single crop and spreading production and price risks, helping to ensure a stable food supply throughout the year. In this paper, we study the role of agricultural credit in increasing farmers' access to improved agricultural technologies such as hybrid seeds and chemical fertilizers, and how the increased food productivity resulting from the increased use of these improved inputs can have beneficial impacts on smallholder farmers' food security and resilience.

The first hurdle in this transformative process is expanding credit access and utilization. Credit rationing is a reality among rural smallholders in many low-income economies leading to very low uptake of credit (Kramer et al., 2024; M. Ndegwa et al., 2020). Credit rationing frequently manifests itself in one of two primary forms: quantity (supply-side) rationing and risk (demand-side) rationing. In the case of the former, lenders restrict borrowers' access to credit because they are deemed insufficiently credit worthy or borrowers' lack the requisite collateral to secure the loan. Consequently, borrowers are involuntarily excluded from credit markets or are limited to borrowing an amount less than they would ideally want to borrow. In the case of the latter, lenders transfer substantial contract risk onto the borrower (in the form of high interest rates, excessive collateral requirements, burdensome documentation, or inflexible contract terms) that the borrower voluntarily withdraws from the credit market altogether. In both cases, the credit market frictions result in socially sub-optimal levels of borrowing. Indeed, credit rationing has been associated with poor productivity, low welfare/living standards, and poverty traps (Baiyegunhi et al., 2010; Boucher et al., 2009; Fletschner et al., 2010; Guirkinger & Boucher, 2008; Zimmerman & Carter, 2003).

Once credit rationing has been overcome, a substantial body of evidence shows that access to rural credit in developing economies enhances agricultural investment and productivity. Foundational studies (e.g., Binswanger & Rosenzweig, 1986; Feder et al., 1990; Petrick, 2004; Zeller et al., 1998) document how alleviating liquidity constraints enables farmers to invest in high-quality inputs and adopt improved technologies. More recent work confirms that credit access facilitates broader capital formation and complementary investments in agriculture.

The Green Revolution, driven by the uptake of high-yielding varieties (HYVs), fertilizers, irrigation, and mechanization, led to significant gains in farm output (Evenson & Gollin, 2003). The emergence of genetically modified (GM) crops has further advanced this trajectory, often referred to as a second Green Revolution. For example, adoption of Bt cotton significantly reduced pesticide application while improving productivity and farm profits among smallholders in India (Gruere & Sun, 2012; Krishna & Qaim, 2012)) and Pakistan (Ali & Abdulai, (2010)). Similarly, GM rice and other transgenic crops are increasingly viewed as critical tools for overcoming climate and pest-related constraints in smallholder systems (Demont & Stein, 2013; Huang et al., 2005;

Juma Calestous, 2015). Other technologies—such as mechanization (Pingali, 2007), chemical inputs (Abdallah et al., 2019; Martey et al., 2019; Nkegbe, 2018), and irrigation (Emerick et al., 2016; Schoengold & Zilberman, 2007)—have all contributed to improved technical efficiency.

Importantly, credit markets are a key enabler of these innovations, allowing farmers to overcome liquidity constraints and finance their adoption. A growing body of evidence demonstrates the direct role of credit in enhancing productivity, revenues, and labor returns (e.g., Abdallah et al., 2019; Dong et al., 2010; Iddrisu et al., 2017; Kramer et al., 2024; Muhamma & Jan, 2011; M. K. Ndegwa et al., 2024; Nordjo & Adjasi, 2019; Si et al., 2021), reinforcing the link between financial access and agricultural innovation. Credit markets can play a multiplicative role in agricultural modernization, as the adoption of one innovation may crowd in complementary investments in other inputs and practices (e.g., Emerick et al., 2016, on flood-resistant rice).

Despite well-known linkages between agricultural credit, increased investments in agricultural technologies, and increased productivity, the literature on the role of credit in promoting higher-order developmental outcomes is comparably thin. To the extent that the literature addresses the impact of credit market access on individual or household welfare, they tend to focus on lower-level outcomes such consumption expenditure (e.g., Atamja & Yoo, 2021; Bocher et al., 2017; Quach & Mullineux, 2007; Tran et al., 2016) or food security, typically measured as the number of meals consumed per day per adult member of a household (Bocher et al., 2017). The literature gap on how agricultural credit can enhance higher-order development outcomes such as resilience among rural households is stark. We believe that one of the main reasons for this gap in literature is due to the challenges associated with measuring household resilience. Indeed, while most economists would have an intrinsic understanding of resilience, we might be hard pressed to formalize a definition of resilience that would easily lend itself to direct measurement. Most studies that assess households' resilience fail to identify resilience as a capacity outcome separate from but related to well-being.

There is a relatively recent – but thin – literature on advanced approaches of measuring resilience as a variable distinct from welfare or well-being indicators (Barrett & Constas, 2014; Zaharia et al., 2021), hence allowing for further analysis of household resilience as a higher-level development outcome. The main differences in the proposed methods depend on their conceptualization of resilience. Barrett & Constas (2014) look at resilience as the ability of an individual or household to avoid falling into poverty and hence measure resilience as the probability that the individual or household achieves or surpasses a minimum acceptable welfare threshold. This is related to the earlier literature on measuring vulnerability as expected poverty (e.g., Chaudhuri, 2003; Christiaensen & Subbarao, 2005; Hoddinott & Quisumbing, 2010; Ward, 2016), though this approach effectively treats resilience as reciprocal to vulnerability. Zaharia et al. (2021), on the other hand, consider resilience as the ability of an individual, household or community to recover after a decline in well-being and hence present resilience measurement methods based on asymmetric mean reversion approaches commonly used in financial markets (Nam et al., 2001, 2002, 2003; Serletis & Rosenberg, 2009). Both of these approaches are useful in helping economists and development practitioners in better understanding and measuring resilience, and could provide valuable guidance to policymakers in conceiving interventions aimed at building resilience and in program evaluation for both state and non-state actors.

In this paper, we quantify households' resilience using a coping strategy index (CSI), specifically their resilience to food insecurity. Food security resilience has been alluded to in development literature but mostly measured with some food security index as a well-being outcome, as opposed to a distinct metric of resilience. We adopt Barrett & Constas' (2014) definition of resilience as a household's capacity over time of avoiding poverty in the face of various stressors and in the wake of myriad shocks. If and only if that capacity is and remains higher over time, then the household is deemed resilient. We follow Cissé & Barrett's (2018) approach to empirically measure and analyze households' food security. We compute a continuous/fractional measure of food security resilience, which is best interpreted as the probability of a household to achieve and surpass a normative minimum CSI level, and a dummy resilience indicator equal to one if that probability is at least equal to a minimum level below which households' resilience capacity is deemed as chronically low. To the best of our knowledge, this is the first time such approaches are being applied to measure households' food security resilience, particularly among the rural smallholders of SSA and other low-income countries.

We also contribute to the scant literature on the role of agricultural credit in promoting rural households' resilience, including food security resilience. Most studies attempting to address this relationship have failed to consider resilience as separable from lower-level outcomes such as well-being or welfare (often proxied by consumption expenditures), and consequently other studies have examined the influence of credit on these other outcomes. We use experimental data from smallholder households in Kenya to fill this gap. We compare two types of credit products (a traditional credit product and a novel insurance-linked credit product) which were the main treatment arms in a randomized control trial (RCT) conducted in Machakos county of Kenya that began in 2017 and remains ongoing. The insurance-linked credit product (risk-contingent credit, or RCC) is distinct from traditional credit (TC) in that it embeds an index insurance product that could compensate the lender in the event of an indemnifiable event that might otherwise imperil the borrowers' ability to repay their loan, thus providing some protection against default – an attractive feature from the perspectives of both borrower and lender (Shee et al., 2015, 2019; Shee

& Turvey, 2012). The embedded insurance component also alleviates the need for collateral, which may help with overcoming both supply- and demand-side credit constraints.

Our results indicate generally low levels of resilience among the respondents, but importantly, access and uptake of production credit positively influenced food security resilience among the sampled households. The results lead us to conclude that proper measurement of resilience is key for effective intervention and appropriate impact evaluation, and we argue that expanding access to credit should be considered as a viable route to strengthening households' resilience.

The rest of the paper proceeds as follows. Section 2 presents the study design where we discuss the data, treatments, experimental design, study area and sampling strategy. Section 3 details how we measure resilience and the processes followed in computing our main outcomes while Section 4 uses the computed outcomes to assess the level of resilience among the participants. Section 5 presents the empirical strategy employed in producing the main results for this paper. Section 6 presents the descriptive statistics characterizing the sample, with detailed discussions on covariate balancing. Section 7 presents the results, discussing the effect of RCC and TC on food security resilience among rural households. Finally, Section 8 presents the conclusion and policy implications of the study, including recommendation for further research.

2 Data, experimental design and sampling strategy

2.1 Data

The data used in this study are drawn from three rounds of household-level experimental panel survey conducted among 1053 households distributed equally across two treatment and one control groups. The baseline survey was conducted in May/June 2017. This was followed by the first phase of RCC and TC lending operations during the 2017/2018 long rain season occurring from October

2017 to January 2018. Treatment households were allowed about five months after the season end to repay their loan, ensuring that they did not have to sell their produce soon after harvesting when there is a glut in the market and prices are low. The midline survey was conducted in May/June 2018. The second phase of lending operations covered the 2019/2020 long rain season occurring from October 2019 to January 2020, and a similar five-month extension was given to allow the farmers enough time to repay their loans. This was followed by the endline survey. For consistency, we intended to hold the end-line survey in May/June 2020 but this was disrupted by the COVID-19 pandemic. Instead, we conducted the endline survey in August/September 2020

All surveys were conducted using a structured, pretested questionnaire. Baseline and midline surveys were conducted as face-to-face interviews in the field by a team of 30 trained enumerators and supervisors. Due to COVID-19 pandemic disruptions, the endline survey was conducted as a streamlined phone survey by a smaller team of 17 trained enumerators. The duration of this phone survey was significantly reduced to fit a 30-minute window, but we ensured all essential survey questions were retained to facilitate the subsequent impact evaluation.[1] All the data for this study were collected electronically using computer-assisted personal interviewing (CAPI) technologies, where the questionnaires were programmed into tablets using CSPro for baseline and SurveyCTO for both mid and endline surveys.

2.2 Treatments and experimental design

This study involves two treatment arms, namely RCC and TC. As previously discussed, RCC embeds an index insurance product within a conventional credit product. The insurance linked to

[1] To reduce survey time during the phone-based endline survey, several modules were shortened or excluded, including detailed questions on household assets, dietary diversity, household demographics, farm characteristics, gender roles, and community leadership. Simplified versions of the food security, credit access, and credit rationing modules were retained to ensure consistency on core variables essential for longitudinal analysis.

credit in this RCT was based on rainfall measures for the traditional long rain season in Machakos County from October 15 to January 15, as described in Shee et al (2019). In brief, historical dekadal (10-daily) rainfall data from 1981 to 2020 were collected for each of the 11 divisions of Machakos County. Cumulative rainfall measures were fit to a PERT distribution, with a cumulative rainfall 'trigger' set at the 20th percentile for each sub-county.[2] Correlated Monte Carlo simulation was used to compute actuarial rates assuming Ksh 300 tick value for every millimeter of rainfall below the trigger. The tick value was determined by the amount required to pay off the loan principal in a worst-case scenario.

After the baseline survey in 2017, we initiated two rounds of lending operations over the long rain seasons in 2017/2018 and 2019/2020. Randomization in the experiment was conducted at the individual household level at the onset of the first round of lending operations using public lotteries. Households were randomly assigned to one of three groups: a control group (not eligible for loans from our intervention partner, Equity Bank, but free to borrow elsewhere), a TC treatment group (eligible to apply for a traditional credit loan from Equity Bank but not for RCC), and an RCC treatment group (eligible to apply for a risk-contingent credit loan but not for TC). Each group comprised of 351 households, and the experimental arms were maintained during the second phase of lending operations. Importantly, being allocated to one of the treatment arms did not guarantee that the household would be approved for or take TC or RCC. Equity Bank was allowed to scrutinize applicants' creditworthiness, and had the authority to reject applications. Likewise, study participants could opt not to apply for credit.

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[2] The PERT (Program Evaluation and Review Technique) distribution is a special case of the beta distribution characterized by three parameters: a minimum, a maximum, and a mode. Unlike the triangular distribution (which is also characterized by these same three parameters), the PERT distribution creates a smooth distribution that closely approximates the normal or lognormal distribution (but with a finite support).

2.3 Sampling process

The study site – Machakos county, Kenya – was purposively selected due to its semi-arid agroecology and location in Equity Bank's coverage area. A multi-level stratified sampling approach was then used to select lower study area units and sample households. First, five out of 11 sub-counties and 13 locations from the 5 locations were purposively selected in consultation with Equity Bank and local administration. This excluded urban and peri-urban areas and considered the Bank's coverage and capacity to execute lending operations. Next, six villages per location were randomly selected from sampling frames comprising all eligible villages per location. Lastly, 15 households per village were randomly selected from village-level households sampling frames giving us 90 households per location and 1170 in total. Table 1 shows the basic demographics of the sampled farmers.

Table 1: Sample demographics

Variable	Observations	Mean	Std. Dev.	Min	Max
Household head is male	1053	0.791	-	0	1
Age of household head (years)	1053	56.185	13.237	22	93
Years of formal education	1053	8.617	3.868	0	17
Dependency ratio	1053	80.141	77.175	0	700
Credit rationed household	1049	0.520	-	0	1
CRRA risk coefficient	1053	0.404	0.230	0	1

3 Measuring household resilience

As previously mentioned, we assess households' resilience in the context of food security using the coping strategy index (CSI), a conventional method of measuring household food insecurity. To construct the CSI, households could select from among a pre-identified list of eight strategies that households could apply to cope with food insecurity. We then created a binary variable for each coping strategy that took a value of one if the strategy was applied at least once in the past seven days and zero otherwise. The CSI measure is then the sum of these eight binary indicators, and could take a value between 0 and 8. In its original form, higher scores in the scale would imply deteriorating food security, since higher scores would indicate that households had to rely on more of these coping strategies. For ease of interpretation within the resilience measurement context, we reversed the index such that lower scores indicate low food security and vice-versa.

To measure resilience, we apply the development resilience approach proposed by Barrett & Constas (2014) and follow Cissé & Barrett's (2018) empirical methods of measuring and estimating household resilience. In their method, household resilience can be presented as a conditional moment function for some dimension of well-being such that:

$$m_i^k\left(W_{it} | W_{i,t-s}, X_{i,t=0}, \varepsilon_{it}\right) \tag{1}$$

where m_i^k is the k^{th} moment of household i's well-being (W) in period t, which is itself a function of well-being in past periods (W_{t-s}), a set of household socioeconomic covariates, X measured at baseline ($t = 0$) and a stochastic idiosyncratic error term ε_{it}. As such, a specific household's well-being is a random variable with its own distribution in each time period. The development resilience approach proposed by Barrett & Constas (2014) and Cissé & Barrett (2018) draws its methodological aptness from integrating the strengths in poverty traps and vulnerability measurement literature (Barrett & Carter, 2013; Carter & Ikegami, 2007). As with poverty traps and vulnerability estimation literature, the approach starts by estimating the first moment, the conditional mean of some dimension of well-being. As is common in the poverty dynamics literature (but typically absent from the vulnerability measurement literature), the approach allows for non-linearity in the expected well-being path dynamics, reflected in high-order polynomial in $W_{i,t-s}$ (Lokshin & Ravallion, 2004; Barrett et al., 2006; Antman & McKenzie, 2007; Cissé & Barrett, 2018). As is typical in the vulnerability measurement literature (but frequently ignored in the poverty dynamics literature), the approach allows for heteroskedasticity in estimated path dynamics and hence, in addition to conditional mean, estimates the conditional variance of the households' well-being (Cissé & Barrett, 2018).[3,4] We make the assumption that our food security scores at time $t-1$ is gamma distributed and hence, the conditional mean and conditional variance are sufficient to model the household and time-period-specific well-being probability density function (p) and the associated complementary cumulative density function ($q = 1-p$).

Following Cissé & Barrett (2018), we estimate household food security scores as a polynomial function of lagged food security scores. Including lags in the estimation allows for the persistent impact of past food insecurity on future food insecurity. Food (in)security is intrinsically a state indicator that summarizes prior states (subject to random perturbations), so including only a single lag in a first-order Markov process is sufficient. Furthermore, while fully addressing possible autocorrelation in the errors of panel data, a single lag is economical in terms of the number of rounds of panel data available for analysis, which diminishes with higher lags. This is particularly important in our case with only a 3-period panel. We use a fourth order polynomial in one-period-lagged food security to estimate household i's food security score at time t (W_{it}):

$$W_{it} = \alpha + \sum_{q=1}^{n=4} \beta_{Mq}\left(W_{i,t-1}\right)^{q} + \delta_M X_{i,t=0} + \varepsilon_{Mit} \tag{2}$$

[3] Although the vulnerability literature frequently assumes conditional heteroskedasticity in path dynamics, many early applications measured vulnerability with cross-sectional data. This was often out of necessity due to the limited availability of longitudinal data in developing countries two or more decades ago. Researchers would have to assume that cross-sectional variation was a reasonable proxy for intertemporal variation.

[4] In addition to permitting heteroskedasticity in welfare path dynamics, this approach is flexible enough to permit non-constant higher-order central moments such as skewness and kurtosis, depending on the assumptions made about the distribution of the well-being variable W_{it}.

As shown in equation (2), W_{it} is also modeled as a function of a vector of other household socioeconomic covariates measured at baseline ($X_{i,t=0}$). The included covariates are the sex of the household head (male=1), age and squared age of the head, years of formal education of the head, dependency ratio (calculated as the number of children under the age of 15 and adults over the age of 65 divided by the number of working-age individuals between 16-65 years of age), credit rationing, and risk aversion measured with constant relative risk aversion (CRRA) coefficients.[5] We also include a binary variable indicating the household had experienced a serious drought during the previous season/period which would effectively have major ramifications on households' food security ex-post.

Following Just & Pope (1979), Antle (1983), and Cissé & Barrett (2018), we store the residuals from the mean food security scores equation above, square them, and use these values to estimate the conditional variance:

$$\sigma_{it}^2 = \alpha + \sum_{q=1}^{n=4} \beta_{Vq}\left(W_{i,t-1}\right)^q + \delta_M X_{i,t=0} + \varepsilon_{Vit} \tag{3}$$

The logic with this specification is that the residuals are consistent estimates of the standard deviation (σ) equivalent, and hence their squared values are consistent estimates of the variance equivalent (σ^2). The conditional variance is also estimated as a 4th-order polynomial function of

[5] A household's credit rationing status is reflected in binary variable equal to one if a household is either risk- or quantity-rationed and equal to zero if otherwise (non-constrained). Risk-rationing is a form of demand side rationing where farmers voluntarily withdraw themselves from the credit market due to fear of losing collateral. Quantity-rationed is a form of supply side rationing implying financial institutions rationing their credit supply where farmers either get less credit than they requested for or are denied credit altogether. Farmers are considered non-constrained if they were either being approached by banks to take credit, would receive credit in the full amount they would request, or did not require credit because of sufficient liquidity. See Boucher et al. (2009), Shee et al. (2018), and Ndegwa et al. (2020) for further details on this credit rationing categorization approach.

one-period-lagged food security scores, selected household socioeconomic covariates and drought shock in the previous time period.

Table 21 presents the food security (CSI) and its variance estimations from equations (1) and(3), respectively. It further displays the heterogenous welfare marginal effects estimates by displaying the results at 10th, 50th, and 90th percentile of the empirical distribution of one-period-lagged CSI (i.e., food insecurity at time $t-1$). From panel (1) on the left, we see that the marginal effect of the lagged CSI on CSI in the current period indicates that food security dynamics are significantly nonlinear, with marginal effects being positive, of substantial overall magnitude, and statistically significant estimate at lower levels (10th percentile, meaning the 10 percent most food insecure) and negative, of even greater overall magnitude, albeit no statistically significant at high levels (90th percentile, meaning the 10 percent most food secure). From panel (2) on the right, although lagged CSI did not significantly affect variance of CSI at time t, there is evidence of nonlinearity in the autoregressive conditional variance where the marginal effect of lagged CSI on conditional variance of CSI at time t was about 78% larger at high (90th percentile) CSI lag values. Further, food security well-being improved with education level of the household head. As expected, in the year following a major drought, households were more likely to face increased food insecurity, though the marginal effect is roughly the same across the distribution of CSI. Experiencing a drought also increased the variance in households' food security, with the effect diminishing and becoming not statistically significant as the household's food situation becomes more secure. Credit rationing increased the variance of CSI non-linearly, increasing CSI variance more prominently among those with low (10th – 50th percentiles) CSI scores than among those with high CSI scores.

Since we assume the random error term ε_{it} from equation (2) is mean zero, the fitted values from estimating the equation gives us the conditional mean:

$$\widehat{W}_{it} = E\left[W_{it} | W_{i,t-1}, X_{it}\right] \tag{4}$$

Similarly, the fitted values from equation (3) gives us the conditional variance:

$$\widehat{\sigma_{it}^{2}} = E\left[W_{it} | W_{i,t-1}, X_{it}\right] \tag{5}$$

With the two fitted parameters, conditional mean and conditional variance, and the gamma distribution assumption, we estimate households' CSI probability density function (pdf) for each period. Following Bury (1999) and Cissé & Barrett (2018), the shape and Y-scale parameters for the gamma distributed well-being are:

$$W_{it} | W_{i,t-1} \sim \Gamma\left(\frac{\widehat{\sigma_{it}^{2}}}{\widehat{W}_{it}}, \frac{\widehat{W}_{it}^{2}}{\widehat{\sigma_{it}^{2}}}\right) \tag{6}$$

Using the computed household- and time-specific pdfs, we then estimate each household's probability of achieving a normative well-being (minimum food security score) ($\underline{W}$) in each period. Resilience q for household i in period t (q_{it}) is simply the household-specific complementary cumulative probability beyond the threshold at time t, and hence a fractional variable (Cissé & Barrett, 2018).

Table 2: Marginal effects of CSI lag and select covariates on CSI and its variance

Variables	Panel 1			Panel 2		
	CSI			Variance (CSI)		
	10th Percentile	50th Percentile	90th Percentile	10th Percentile	50th Percentile	90th Percentile
CSI lag	0.4129***	0.3700***	-0.9672	-0.1326	-0.2928	-0.9159*
	(0.143)	(0.087)	(1.131)	(0.275)	(0.187)	(0.512)
Took credit	-0.115	-0.1226	-0.1174	0.3222	0.2997	0.1431
	(0.113)	(0.121)	(0.118)	(0.297)	(0.280)	(0.166)
Male headed household	0.0466	0.0497	0.005	0.0951	0.0884	0.0422
	(0.174)	(0.186)	(0.178)	(0.449)	(0.420)	(0.196)
Head age	-0.0574*	-0.0612*	-0.0586*	0.0266	0.0247	0.0118
	(0.032)	(0.034)	(0.032)	(0.087)	(0.081)	(0.042)
Head age sqr	0.0005*	0.0006*	0.0006*	-0.0004	-0.0003	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Head education yrs	0.0522***	0.0556***	0.0532***	-0.0738	-0.0686	-0.0328
	(0.017)	(0.018)	(0.019)	(0.049)	(0.048)	(0.033)
Dependency ratio	-0.0001	-0.0001	-0.0001	0.0006	0.0005	0.0003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Credit rationed	-0.1145	-0.122	-0.1168	0.6079**	0.5653*	0.2701
	(0.116)	(0.124)	(0.120)	(0.304)	(0.306)	(0.207)
CRRA coeff	0.0722	0.077	0.0737	-0.4911	-0.4567	-0.2182
	(0.247)	(0.264)	(0.252)	(0.590)	(0.550)	(0.324)
Year after major drought	-0.6178***	-0.6587***	-0.6304***	1.7998***	1.6738***	0.7996
	(0.145)	(0.156)	(0.168)	(0.399)	(0.401)	(0.508)

*Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

4 Assessing the resilience levels

In Figure 1, we assess the distribution of our sample at varying levels of threshold food security $\underline{W}$ from 1 (very food insecure) to 8 (very food secure). At low levels of $\underline{W}$, the vast majority of households would be deemed rather quite resilient, as they largely have a greater than 50 percent probability of their CSI score exceeding the threshold. Households' resilience decreases as the minimum threshold rises, since it becomes more difficult for households to attain minimum thresholds that are indicative of a high degree of food security. By the time the minimum threshold reaches $\underline{W} = 4$, all of the households lie below the 0.5 complementary cumulative probability, meaning no household has greater than 50-50 odds of attaining a minimum degree of food security (at this threshold). When $\underline{W}$ is raised to 8, no household has greater than a 30 percent probability of attaining this threshold level of food security. This signifies generally low resilience among the households. To proceed with our analysis, we require a fixed threshold against which to compute participants' probability of exceedance. Obviously, the choice of threshold is subjective, and as we have just discussed above, this choice is almost certain to impact the results. Fortunately, Figure 1 provides some evidence that would allow for relatively unambiguous prediction for how results might be qualitatively different under an alternative threshold. We set the normative food security level at 5, which coincides with the 25th percentile of the observed CSI scores. We however conduct sensitivity analysis to check the robustness of our results to this subjective choice – we estimate treatment effects on resilience computed at all levels of $\underline{W}$ and keep the result tables in the appendix. This analysis generates consistent results at different levels of $\underline{W}$, implying that our findings are robust to the subjective choice of $\underline{W}$.

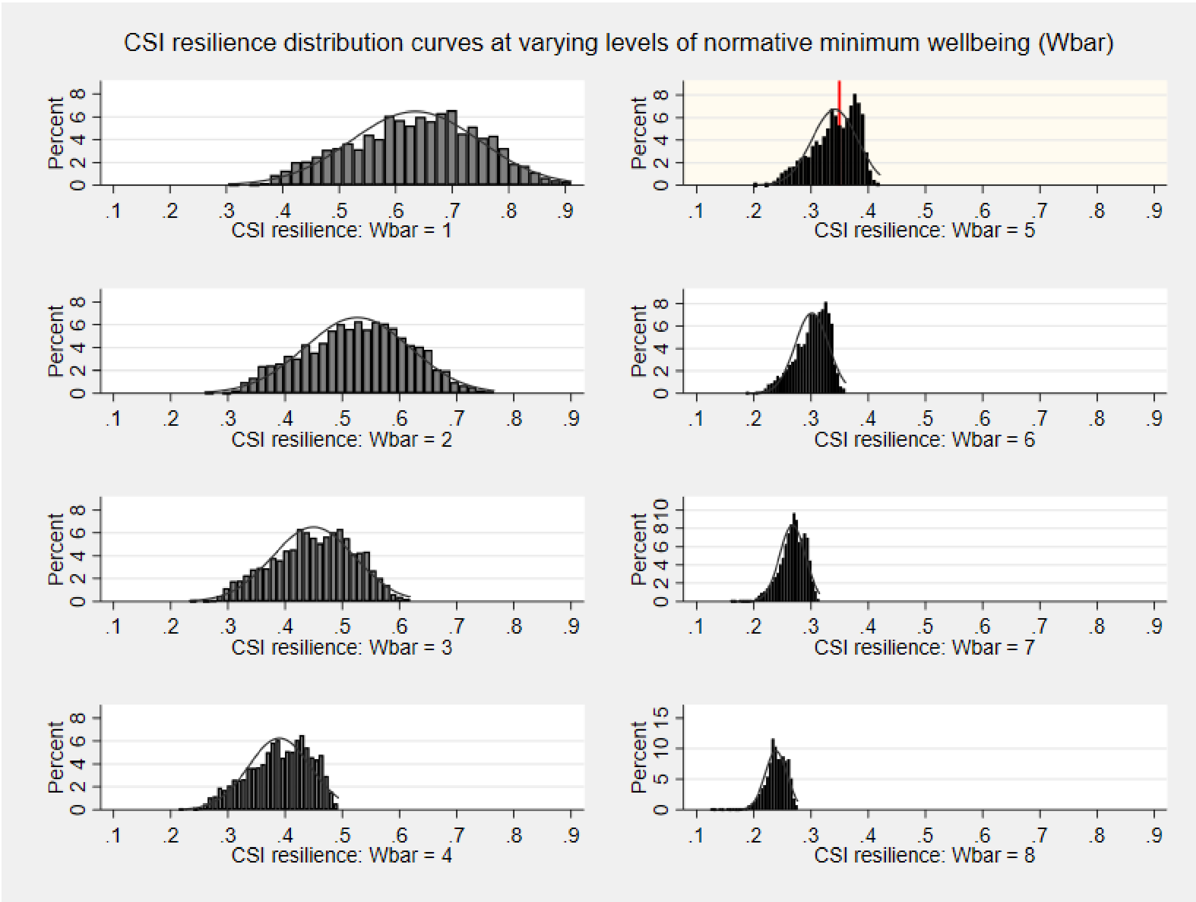
Further, we create a secondary binary variable $\widehat{q_{it}}$ to classify a household as either resilient or not such that

$$\widehat{q_{it}} = \begin{cases} 1 \text{ if } q_{it} \geq \underline{p} \\ 0 \text{ otherwise} \end{cases} \tag{7}$$

where $\underline{p}$ is the reference threshold probability below which we consider a household's probability (q_{it}) of reaching or surpassing the minimum food security threshold $\underline{W}$ intolerably low (Cissé & Barrett, 2018). Again, the selection of this threshold probability for qualifying resilience is necessarily subjective. We ideally want a threshold probability such that resilience (or lack thereof) could be due to either a high level of food security (low level of food insecurity) *or* a low degree of food security variance (high degree of food security variance).[6] We subjectively set our $\underline{p}$ at 0.35 and hence households whose probability of reaching $\underline{W} = 5$ was greater than or equal to 0.35 were defined as resilient, while those whose probability of reaching $\underline{W} = 5$ was less than 0.35 were considered as unresilient. The 0.35 threshold is displayed with a red vertical reference line on the $\underline{W} = 5$ diagram in Figure 1. We therefore proceed with two measures of resilience: fractional response q_{it} (the probability of exceeding $\underline{W} = 5$) and binary response $\widehat{q_{it}}$ (indicating whether or not a household's probability of exceeding $\underline{W} = 5$ was greater than 0.35). These two measures of resilience serve as our outcome variables as we now proceed to estimate the treatment effects of RCC and TC on households' food security resilience.

[6] In the vulnerability measurement literature, the analogous threshold probability is the probability that incomes in some future period would fall below a poverty line. This threshold was commonly set at 0.5, implying that a household was vulnerable if they had a 50 percent probability of poverty at some point in the future. An implication of this threshold is that as the time interval collapses to zero, the statuses of "currently poor" and "currently vulnerable to poverty" coincide. Using this threshold restricts vulnerability to only those households with low expected income, ignoring the possibility that households could be vulnerable to poverty due to highly variable income.

Figure 1: Sample distributions of CSI complementary cumulation probabilities at varying levels of ($\bar{W}$)



5 Empirical strategy

Our main aim in this paper is to assess the role of agricultural credit in promoting households' food security resilience. We compare two types of credit, namely RCC and TC. For robustness in the reported causality (credit uptake effects), we employ two different econometric estimation approaches namely: entropy balancing for causal effects (estimated with treatment weights) and local average treatment effects (LATE) via two-stage least squares (2SLS) with random assignment as the excluded instrument. We also report the intent-to-treat (ITT) effects estimated via OLS and logit, which, although important for policy purposes, are mostly attenuated by imperfect compliance common in RCTs and hence tend to underestimate the actual treatment effects of an intervention (Abadie & Cattaneo, 2018; Angrist, 2006; Duflo et al., 2007; Soderbom et al., 2015). There was substantial noncompliance in this study, particularly among the treatment groups, with credit uptake of 32% and 16% during the first and second intervention phase, respectively.[7] Consequently, to the extent that credit uptake has beneficial impacts on food security, the ITT estimates are likely to provide considerably understated treatment effects. Nevertheless, since these ITT estimates provide a measure of the average effects in treatment households (regardless of whether individuals borrowed money through this project), they may provide more of a lens into the types of economy-wide impacts that could be expected with the expansion of agricultural credit across the rural landscape in Kenya.

Following Cissé & Barrett (2018), we first regress the estimated probability of household i achieving or exceeding the minimum CSI threshold $\underline{W}$ (=5) at time t (the fractional response q_{it}) against our treatment arms, namely RCC and TC:

$$q_{it} = \alpha + \delta_1 RCC_{it} + \delta_2 TC_{it} + \beta X_{i,t=0} + \varepsilon_{it} \tag{8}$$

where RCC and TC are binary response variables equal to 1 if a household took the corresponding credit and zero otherwise, X is a vector of households' socioeconomic covariates measured at baseline and ε is the stochastic error term. This was first modeled as a fractional regression with logit link and then, for robustness test, as an OLS estimation. We then estimate a logit model for the binary response $\widehat{q_{it}}$, equal to one if household i is deemed resilient at time t and zero otherwise:

$$\Pr\left(\widehat{q_{it}} = 1 \,\middle|\, TC_{it}, RCC_{it}, X_{i,t=0}\right) = \pi(\alpha + \delta_1 RCC_{it} + \delta_2 TC_{it} + \beta X_{i,t=0} + \varepsilon_{it}) \tag{9}$$

[7] The observed noncompliance likely reflects the study's design, which purposefully selected farmers from the general rural population rather than from among active or recent borrowers. While all participants were randomly assigned to credit groups and invited to informational meetings and trainings, some individuals may have required more time or familiarity to make borrowing decisions. This noncompliance itself highlights the extent of underlying credit rationing in rural Kenya.

where π indicates that the error term (ε_{it}) follows a logistic distribution. One would quickly notice that RCC and TC in Equations (8) and (9) are endogenous, since, although assignment to either treatment arm was random and exogenous, uptake of the offered credit was not since this was left to the households' choice. To control for this endogeneity in credit uptake, we first treat our data as observational data and use the entropy balancing for causal effects approach as proposed by Hainmueller (2012) to control for imperfect compliance (self-selection) bias. Unlike matching methods (including matching based on propensity scores) commonly used to improve the covariate balance between treatment and 'control' group (Rosenbaum & Rubin, 1983; Ho et al., 2007; Sekhon, 2009), entropy balancing involves a reweighting scheme that directly incorporates covariate balance into the weight function that is applied into the sample units (Hainmueller, 2012; Hainmueller & Xu, 2013). We use the overall uptake (equal to one if a household took the credit offered, either RCC or TC, and zero otherwise) as the binary treatment variable for which balancing is needed.

Additionally, we exploit the study's experimental design and estimate ITT effects and LATEs on the continuous and binary measures of resilience. To estimate ITT effects, we use a simple means-difference (SMD) estimator:

$$y_{it} = \alpha + \delta_{SMD_1}\widetilde{RCC}_i + \delta_{SMD_2}\widetilde{TC}_i + \varepsilon_{it} \tag{10}$$

where y_{it} is a measure of household i's food security resilience at time t (either q_{it} or $\widehat{q_{it}}$). We treat q_{it} as a continuous variable and hence estimate ITT effects for this outcome using OLS, while ITT effects for the model with $\widehat{q_{it}}$ as the outcome measure are estimated with the logit estimator. In equation (10), $\widetilde{RCC}$ and $\widetilde{TC}$ are exogenous treatment assignment variables equal to one if a household was randomly assigned to the group for the corresponding credit product and zero otherwise. The SMD parameters of interest are δ_{SMD_1} and δ_{SMD_2} which are the ITT effects for RCC and TC respectively. We estimate the ITT models with and without baseline households' socioeconomic covariates (X).

To control for imperfect compliance and hence estimate the effect of credit uptake on households' food security resilience, we use 2SLS to estimate LATEs. We use random assignment to the treatment arm as the excluded instrument for uptake, a near universal practice in RCTs with self-selection or imperfect compliance (Abadie & Cattaneo, 2018; Angrist & Pischke, 2008; F. L. Huang, 2018; Khandker et al., 2009; Soderbom et al., 2015). In the first stage, uptake of RCC and of TC are regressed against random assignment to either of the credit types or control group. Then, the fitted values of uptake are stored and then included in the second stage as the treatment variables. Food security resilience is estimated in the second stage instrumental variable equation as:

$$y_{it} = \alpha + \delta_{IV1}\widehat{RCC}_{it} + \delta_{IV2}\widehat{TC}_{it} + \varepsilon_{it} \quad (11)$$

where, in addition to already defined components, $\widehat{RCC}_{it}$ and $\widehat{TC}_{it}$ are the respective uptake fitted values from first stage equations while δ_{IV1} and δ_{IV2} are the treatment effects parameters of interest. Like with ITT, LATE models are also estimated with and without baseline households' socioeconomic covariates.

6 Descriptive statistics and covariate balancing

Table 32 presents the mean for the control group and the socioeconomic covariates balancing tests between treatments and control groups. The parenthesis in the control mean column contain standard deviation while all the others contain standard errors from the respective regression estimations.

The balance tests in Panel A assess the effectiveness of our randomization and experimental design. For these tests, we estimated a series of regressions where each selected covariate was regressed against the multinomial treatment assignment variable equal to zero for control, equal to one for RCC and equal to two for TC. Hence, control group is the omitted base category against which we compare the rest. Both the control group and the two treatment groups were statistically similar in almost all the selected covariates with the exemption of dependency ratio. The control group had a dependency ratio of about 87 percent while both RCC and TC groups' dependency ratio was roughly 10 percentage points less. This difference was only marginally significant, with $0.05 < p < 0.10$ for tests comparing both the RCC group and the TC group to the control. Further, we test for joint orthogonality (not in the table) where we model a multinomial logit with treatment category as the outcome variable and the selected baseline covariates as the predictors. The test for joint orthogonality yields a p-value of roughly 0.6 and hence we fail to reject the null hypothesis that the covariates are jointly orthogonal. This insinuates there was no significant selection bias in treatments assignment and any imbalances between treatment and control groups arise solely due to chance. Hence, we can have considerable confidence in the integrity of our experimental design. Nevertheless, to increase the precision of our treatment effect estimates and demonstrate the robustness of our results, we estimate our experimental models both with and without the covariates.

Panel B assess the effectiveness of non-experimental treatment assignment using the treatment weights computed with entropy balancing for causal effects approach. We first regress all the selected baseline covariates against binary variables indicating RCC uptake and TC uptake. The results of these estimations are shown in the 'without treatment weights' columns. The baseline dependency ratio for those who took RCC was 23 percentage points less than the rest. Those who took TC were seven percentage points more likely to be male, and their dependency ratio was 17 percentage points lower than the rest. These statistical differences which would imperil causal inference disappear when the same regression models are estimated with treatment weights. This gives us confidence that the computed weights deliver comparable treatment and control groups and hence inclusion of these weights in our treatment effects estimations deals effectively with the eminent self-selection bias in the uptake of credit.

Table 3: Households characteristics and covariate balancing: Balancing done with experimental and observational data approaches

	Panel A - Experimental data approach			***Panel B - Observational data approach***			
		Treatments versus control		Without treatment weights		With treatment weights	
VARIABLES	Control mean	Assigned RCC	Assigned TC	Took RCC	Took TC	Took RCC	Took TC
Male head	0.78	0.028	0.02	0.043	0.070*	-0.003	0.022
	(0.42)	(0.031)	(0.031)	(0.042)	(0.041)	(0.046)	(0.045)
Head age in years	56.54	0.111	-1.188	-0.251	-2.066	0.3	-1.41
	(13.71)	(0.993)	(1.023)	(1.302)	(1.422)	(1.483)	(1.608)
Head age squared	3,384.65	-17.04	-141.45	-82.744	-255.010*	-6.55	-165.328
	(1,548.70)	(112.525)	(115.463)	(145.707)	(154.462)	(161.091)	(171.082)
Years of education	8.63	-0.071	0.026	0.231	0.691	-0.081	0.282
	(4.04)	(0.299)	(0.292)	(0.384)	(0.433)	(0.420)	(0.470)
Dependency ratio	87.23	-10.441*	-10.822*	-23.221***	-16.595**	-7.416	-1.046
	(87.29)	(6.146)	(5.893)	(7.371)	(7.687)	(7.875)	(8.264)
Credit rationed	0.53	-0.011	-0.016	-0.042	-0.069	0.004	-0.02
	(0.50)	(0.038)	(0.038)	(0.053)	(0.056)	(0.061)	(0.063)
CRRA coefficient	0.40	0.004	-0.001	-0.006	-0.019	0.032	0.016
	(0.24)	(0.018)	(0.017)	(0.025)	(0.026)	(0.030)	(0.030)

*Note: *** p<0.01, ** p<0.05, * p<0.10*

7 The role of RCC and traditional credit in promoting food security resilience

7.1 ITT and LATE effects

Table 43 presents the RCC and TC ITT effects and LATEs on the fractional response (Panel A) and binary response (Panel B) measures of food security resilience. In each of these models, increasing values of the dependent variable indicate higher degrees of resilience, since the fractional response variable indicates the probability that the CSI would exceed the minimum threshold, and the binary response indicates that a household's probability of exceeding the minimum CSI threshold is at least 35 percent. All the models were estimated first without and then with baseline covariates as shown. We also test the null hypothesis that the difference between RCC and TC effects is not different from zero. This was done across all the models and the row for these tests is boldened and italicized.

Considering the ITT columns (in both Panels A and B), random assignment to either RCC or TC had beneficial and statistically significant effects on enhancing food security resilience, both fractional and binary response. Assignment to either of the treatments increased the fractional response food security resilience, the probability of at least achieving $\underline{W} = 5$, by 0.3 percentage points, and this effect size is robust to the inclusion of baseline socioeconomic covariates (though the treatment effect is more precisely estimated when covariates are included). Considering Panel B, assignment to RCC increased the likelihood of being deemed resilient by about 3 percentage points, though this was only statistically significant (with $p < 0.1$) when estimated with baseline covariates. Assignment to TC increased the likelihood of being deemed resilient by about 4.0 percentage points.

As would typically be expected, LATEs are qualitatively similar to ITT effects, though of a considerably higher magnitude. Looking first at the LATE estimates in Panel A, uptake of RCC increased the probability of achieving at least $\underline{W} = 5$ by 1.3 percentage points, while uptake of TC increased the probability of achieving at least $\underline{W} = 5$ by about 1.5 percentage points. Considering the LATE columns in Panel B, uptake of RCC increased the likelihood of being deemed resilient by about 11 percentage points, though this treatment effect is only statistically significant (at $p < 0.1$) when estimated with baseline covariates. Uptake of TC on the other hand increased the likelihood of being categorized as food security resilient by about 20 percentage points and this is statistically significant regardless of whether baseline covariates are included.

Across all the models, we fail to find sufficient evidence to reject the null hypothesis that the difference in RCC and TC treatment effects was different from zero, despite some sizable differences in point estimates. Indeed, point estimates for treatment effects of TC are almost always and everywhere larger than those associated with RCC. This is somewhat surprising given the fact that RCC has an insurance component embedded within its product design, and implicitly insurance should enhance resilience since it allows for the transferal of some production risk. The fact that we can conclude that both RCC and TC influenced food security resilience equally may indicate that simply overcoming liquidity and credit constraints by expanding rural credit markets may enable farmers to invest in productive inputs like seeds and fertilizers that can increase production without substantial downside risks, thereby increasing household food supplies (and thus reducing the number of coping strategies households would have to employ) without concurrently increasing variance.

To check for sensitivity of the desirable treatment effect reported above to the subjective choice of $\underline{W}$, we estimate treatment effect on varying measures of resilience (q_{it}) computed at all levels of $\underline{W}$ – 1 to 8. As shown in Appendix Table A1 and A2, we estimate both ITT and LATE, first excluding baseline covariates (Table A1) and then including them (table A2). The results are largely consistent with what we already reported with $\underline{W} = 5$. When estimated without baseline covariates (Table A1), RCC had positive and significant effect on food security measure computed at almost all levels of $\underline{W}$ except for $\underline{W} = 7$ *and* 8. Similarly, TC had a positive effect on security measure computed at all levels of $\underline{W}$, but the effect was statistically significant only in the case of $\underline{W} = 5$ *and* 6. When estimated with baseline covariates (Table A2), both RCC and TC had positive and statistically significant effect on food security measure computed at all levels of $\underline{W}$ – with the exception of $\underline{W} = 8$ which was positive but not statistically significant.

Table 4: RCC and TC treatment effects from ITT and LATE estimations

VARIABLES	Panel A				Panel B			
	Fractional response resilience				Binary response resilience			
	ITT SMD	ITT SMD	LATE	LATE	ITT SMD	ITT SMD	LATE	LATE
RCC	0.003*	0.004***	0.013*	0.014***	0.028	0.030*	0.106	0.115*
	(0.002)	(0.001)	(0.007)	(0.004)	(0.020)	(0.015)	(0.075)	(0.058)
Traditional credit	0.003*	0.003***	0.015*	0.015***	0.044**	0.042***	0.199**	0.196***
	(0.002)	(0.001)	(0.008)	(0.005)	(0.019)	(0.015)	(0.086)	(0.068)
RCC=TC: Pvalue	***0.967***	***0.886***	***0.687***	***0.652***	***0.333***	***0.336***	***0.199***	***0.166***
Baseline covariates	***No***	***Yes***	***No***	***Yes***	***No***	***Yes***	***No***	***Yes***
Constant	0.249***	0.258***	0.246***	0.256***	-0.672***	-0.648***	-0.700***	-0.665***
	(0.002)	(0.007)	(0.003)	(0.007)	(0.023)	(0.103)	(0.030)	(0.102)
Observations	2,008	2,008	2,008	2,008	2,015	2,008	2,015	2,008
Number of HHID	1,042	1,042	1,042	1,042	1,046	1,042	1,046	1,042
Overall R2	0.575	0.801	0.579	0.809	0.563	0.663	0.562	0.665
Mean of control	.339	.339	.339	.339	.447	.447	.447	.447

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

7.2 Uptake effects estimated with entropy balancing treatment weights

Table 54 presents RCC and TC treatment effects where dataset was treated as observational data and hence treatment effects were estimated with treatment weights computed via the entropy balancing approach. Columns (1) and (2) present the results for the probability that a household achieves or exceeds the normative minimum CSI or $\underline{W}$=5. Column (1) shows results from a fractional outcome regression estimated by maximum pseudo-likelihood, and hence the marginal effects are also presented for ease of interpretation. Column (2) presents results of a similar model estimated by OLS, which we include to demonstrate the robustness of the results. Column (3) reports the results for the binary resilience indicator, where households whose probability of achieving $\underline{W} = 5$ was at least 35 percent were deemed resilient while those whose probability of achieving at least $\underline{W} = 5$ was less than 35 percent were defined as not resilient. For this binary dependent variable model, we estimated a logit regression, and hence report marginal effects from this regression as well for ease of interpretation. All estimations include selected household socioeconomic covariates measured at baseline. Finally, across all the models, we test the null hypothesis that the difference between RCC and TC effects is not different from zero and the row for this test is boldened and italicized.

Consistent with earlier results, the results in Table 4 indicate that uptake of both RCC and TC had beneficial and highly significant effects on enhancing food security resilience. Looking first at the marginal effects for the fractional response regression under column (1), those who took RCC increased their probability of at least achieving $\underline{W} = 5$ by 1.22 percentage points while those who took TC increased their probability of at least achieving $\underline{W} = 5$ by 1.18 percentage points. OLS estimation in column (2) yielded treatment effects which are equivalent to the treatment effects from the fractional response regression in terms of both magnitude and standard errors. Considering the logit regression margins under column (3), uptake of RCC and TC increased the likelihood of being food security resilient by 13.5 percent and 12.6 percent, respectively. Consistent with our earlier results, we do not have sufficient evidence to reject the null hypothesis that RCC and TC have equivalent treatment effects on increasing households' food security resilience. We thus echo our earlier conclusion that the two types of credit products influenced households' food security resilience equally.

Similar to sensitivity checks for ITT and LATE above, we repeat the OLS estimation in Column 2 of Table 4 but for food security measure computed at all levels of $\underline{W}$ – we select the OLS estimation here to represent all the other estimations using the entropy balancing weights since the results were consistent across the models. As shown in Appendix Table A3, the results are consistent with what we already found with $\underline{W} = 5$. Both RCC and TC had positive and statistically significant effect on food security measure computed at almost all levels of $\underline{W}$ – with the exception of RCC's effect on resilience computed with $\underline{W} = 8$, which was still positive but not statistically significant.

As mentioned previously, we have used subjective rules here both to establish a minimum threshold above which households would be deemed to be food secure (namely, $\underline{W} = 5$) as well as to classify whether households are resilient (namely, if their probability of achieving or surpassing $\underline{W} = 5$ was at least equal to 35 percent). Since the magnitude of the results may be sensitive to these subjective choices, we have conducted sensitivity tests which fundamentally yield consistent results. The results reported here are valuable to the extent that they shed more light on the role of credit in promoting food security resilience among the smallholder households.

Table 5: RCC and TC treatment effects from fractional, OLS, and logit regressions with entropy balancing weights

	(1)		(2)	(3)	
	Fractional regression		OLS	Logit regression	
VARIABLES	Coeff	Margins	Coeff	Coeff	Margins
RCC	0.0550***	0.0122***	0.0122***	2.1804***	0.1353***
	(0.008)	(0.002)	(0.002)	(0.382)	(0.024)
Traditional credit	0.0535***	0.0118***	0.0118***	2.0271***	0.1258***
	(0.008)	(0.002)	(0.002)	(0.395)	(0.022)
RCC=TC: Pvalue	***0.7086***		***0.8641***	***0.8641***	
Male household head	0.0189**	0.0042**	0.0042**	1.2048***	0.0748***
	(0.009)	(0.002)	(0.002)	(0.382)	(0.023)
Household head age in years	0.0081***	0.0018***	0.0017***	0.0549	0.0034
	(0.002)	(0.000)	(0.000)	(0.088)	(0.005)
Head's age squared	-0.0001***	-0.0000***	-0.0000***	-0.0012	-0.0001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Head's education in years	-0.0146***	-0.0032***	-0.0033***	-0.4452***	-0.0276***
	(0.001)	(0.000)	(0.000)	(0.059)	(0.003)
Dependency ratio	0.0002***	0.0001***	0.0001***	0.0050**	0.0003**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Credit rationed	0.1108***	0.0245***	0.0246***	2.9619***	0.1838***
	(0.006)	(0.001)	(0.001)	(0.485)	(0.024)
CRRA coefficient	-0.0756***	-0.0167***	-0.0167***	-2.5879***	-0.1606***
	(0.015)	(0.003)	(0.003)	(0.633)	(0.035)
Panel time = 2	0.2760***	0.0611***	0.0621***	7.8624***	0.4880***
	(0.006)	(0.001)	(0.001)	(0.638)	(0.013)
Constant	-1.1417***		0.2352***	-9.8904***	
	(0.059)		(0.013)	(2.596)	
Observations	1,949	1,949	1,949	1,949	1,949
Mean of control	0.339	0.339	0.339	0.447	0.447

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10*

8 Conclusion and policy implications

This paper addresses an important policy issue which has not been examined in literature, namely the role of credit, both insurance-linked and traditional credit, in promoting household food security resilience. Unlike some previous studies, we identify resilience as higher-order dimension of household well-being different but related to other lower-order dimensions of household well-being such as income or wealth. We adapt the innovative approach of measuring development resilience using the conditional moments approach proposed by Barrett & Constas (2014) and further operationalized by Cissé & Barrett (2018). We compute two resilience variables namely fractional response and binary indicator of resilience which we use to further examine whether and to what extent credit enhances households' resilience. Using experimental data from a randomized control trial in Machakos county, Kenya, we rely on simple means difference estimated with OLS to report ITT effects and 2SLS regression methods to report the LATEs to provide insights into the effect of credit uptake on resilience. Further, to demonstrate the robustness of our results from the raw experimental data, we also estimate credit treatment effects with entropy balancing treatment weights. We find generally low resilience among the sampled households, but there is compelling evidence that expanding rural credit markets could have a beneficial impact on enhancing households' resilience to food insecurity. Random assignment to and uptake of either RCC or TC led to improved household resilience. LATEs based on experimental data and treatment effects based on entropy balanced data were consistent, providing a high degree of confidence in our results. Despite important differences in the two products (RCC and TC) we do not find that they yielded differential treatment effects on enhancing resilience, leading us to conclude that alleviating liquidity and/or credit constraints through expanded credit market access may be sufficient to increase households' resilience to food insecurity, at least at the low levels of resilience observed in our sample.

Our findings in this paper have some implications for policy and industry. First, by directly linking credit uptake with household food security resilience, we recommend that the state and non-state actors concerned with building the resilience of rural communities should consider credit for agricultural production as a viable tool. Secondly, considering resilience as either capacity to bounce back after a shock(s) or to not fall (to poor living standards) in the face of shocks, those involved in policy and program formulation to help rural communities cope with major covariate shocks such as drought should consider enhancing credit access for such communities as a way of building their resilience. This extends to households' idiosyncratic shocks, particularly considering that the methods used here to measure resilience do not identify a specific shock but an aggregate of shocks that face a household. Thirdly, although we do not find significant difference between the RCC and TC effects on households food security resilience, recent studies have already indicated that linking insurance to credit leads to higher uptake of agricultural production credits and increased investments in productive inputs (Bellissa et al., 2020; Gallenstein et al., 2021; Mishra et al., 2020; Ndegwa et al., 2020; Ndegwa et al., 2025; Kramer et al., 2024). As such, governments, development agencies as well as financial institutions should consider designing and promoting safer and cheaper investment credits for the rural farming communities as a way of achieving widespread well-being and resilience.

Finally, in this study, we assess food security resilience, but the literature gap is wide. Further areas of related investigation remain. For instance, other forms of resilience beyond food security could be assessed, as well as developing a composite measure of resilience. Further, we do not believe that our assessment of credit influence on resilience is conclusive. Other types of credit and different contexts could be assessed, employing a variety of other research and analytical methods. Similarly, the role of other interventions, besides credit, in building resilience could be assessed. We also recommend similar analysis but with longer experimental panel, especially given that the use of lagged well-being variable to compute resilience left us with two-out of three time periods for analysis.

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Appendices

Table A1: Sensitivity analysis for RCC and TC ITT and LATE – estimated for resilience computed at all levels of W-bar (1 to 8) – without baseline covariates

Variables	(1) W-BAR1 ITT	(2) W-BAR1 LATE	(3) W-BAR2 ITT	(4) W-BAR2 LATE	(5) W-BAR3 ITT	(6) W-BAR3 LATE	(7) W-BAR4 ITT	(8) W-BAR4 LATE	(9) W-BAR5 ITT	(10) W-BAR5 LATE	(11) W-BAR6 ITT	(12) W-BAR6 LATE	(13) W-BAR7 ITT	(14) W-BAR7 LATE	(15) W-BAR8 ITT	(16) W-BAR8 LATE
RCC	0.011*	0.042*	0.009*	0.034*	0.007*	0.026*	0.005*	0.019*	0.003*	0.013*	0.002	0.008*	0.001	0.004	0	0.001
	(0.006)	(0.023)	(0.005)	(0.018)	(0.004)	(0.014)	(0.003)	(0.01)	(0.002)	(0.007)	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)	(0.004)
Traditional credit	0.008	0.038	0.007	0.031	0.005	0.024	0.004	0.019	0.003*	0.015*	0.002*	0.011*	0.002	0.007	0.001	0.004
	(0.006)	(0.027)	(0.005)	(0.021)	(0.003)	(0.016)	(0.003)	(0.012)	(0.002)	(0.008)	(0.001)	(0.006)	(0.001)	(0.004)	(0.001)	(0.004)
Observations	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008
Overall R^2	0.462	0.464	0.486	0.488	0.515	0.518	0.549	0.552	0.575	0.579	0.564	0.567	0.458	0.461	0.249	0.251
Baseline covariates	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Mean of control	.627	.627	.52	.52	.445	.445	.386	.386	.339	.339	.3	.3	.267	.267	.239	.239

*Note: Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table A2: Sensitivity analysis for RCC and TC ITT and LATE – estimated for resilience computed at all levels of W-bar (1 to 8) – with baseline covariates

Variables	(1) W-BAR1 ITT	(2) W-BAR1 LATE	(3) W-BAR2 ITT	(4) W-BAR2 LATE	(5) W-BAR3 ITT	(6) W-BAR3 LATE	(7) W-BAR4 ITT	(8) W-BAR4 LATE	(9) W-BAR5 ITT	(10) W-BAR5 LATE	(11) W-BAR6 ITT	(12) W-BAR6 LATE	(13) W-BAR7 ITT	(14) W-BAR7 LATE	(15) W-BAR8 ITT	(16) W-BAR8 LATE
RCC	0.01***	0.040***	0.008***	0.033***	0.007***	0.026***	0.005***	0.019***	0.004***	0.014***	0.002***	0.009***	0.001*	0.005*	0.001	0.002
	(0.004)	(0.014)	(0.003)	(0.011)	(0.002)	(0.008)	(0.001)	(0.006)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Traditional credit	0.008**	0.039**	0.007**	0.032**	0.005**	0.025***	0.004***	0.02***	0.003***	0.015***	0.002***	0.011***	0.002**	0.007**	0.001	0.004
	(0.004)	(0.017)	(0.003)	(0.013)	(0.002)	(0.01)	(0.001)	(0.007)	(0.001)	(0.005)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)
Observations	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008
Overall R^2	0.724	0.731	0.745	0.753	0.770	0.779	0.795	0.803	0.801	0.809	0.751	0.758	0.585	0.590	0.327	0.329
Baseline covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of control	.627	.627	.52	.52	.445	.445	.386	.386	.339	.339	.3	.3	.267	.267	.239	.239

*Note: Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table A3: Sensitivity analysis for RCC and TC uptake effect estimated with entropy balancing weights – estimated for resilience computed at all levels of W-bar (1 to 8) – with baseline covariates

Variables	(1) W-BAR1	(2) W-BAR2	(3) W-BAR3	(4) W-BAR4	(5) W-BAR5	(6) W-BAR6	(7) W-BAR7	(8) W-BAR8
Took RCC	0.037***	0.030***	0.023***	0.017***	0.012***	0.008***	0.004***	0.002
	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Took TC	0.033***	0.027***	0.021***	0.016***	0.012***	0.008***	0.005***	0.003**
	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	1949	1949	1949	1949	1949	1949	1949	1949
R^2	0.707	0.731	0.754	0.775	0.781	0.741	0.594	0.334
Baseline covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of control	.627	.52	.445	.386	.339	.3	.267	.239

*Note: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

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