



Distributional impact of climate-smart villages on access to savings and credit and adoption of improved climate-smart agricultural practices in the Nyando Basin, Kenya

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Abstract

Adoption of improved livestock breeds requires, as with other climate-smart agricultural (CSA) practices, upfront investments, which might be a significant barrier for smallholders. For this reason, the climate-smart village (CSV) approach not only includes CSA interventions, but also interventions to improve access to savings and credit among smallholders by means of a community-based approach. In this paper we study smallholders in CSVs in Kenya who were encouraged, among others, to adopt improved livestock breeds for crossbreeding with indigenous breeds to improve their resilience to climate change and variability. The farmers were also encouraged to become part of savings and credit groups to improve smallholder access to finance. The objective of this paper is thus to determine the (distributional) impact of CSVs on access to savings and credit and the adoption of improved CSA practices. Due to the as good as random selection of CSVs, we are able to estimate the treatment effects on the treated for the smallholders who decided to participate in the CSA intervention by means of a linear probability model. The analysis is based on a balanced panel of 118 farm households interviewed in 2017, 2019, and 2020. The main findings of this study are that the CSV intervention increased the adoption of improved livestock breeds. It also stimulated the membership of savings and credit groups which in turn stimulated the adoption of improved livestock breeds. These findings point to the importance of community-based savings and loan initiatives to mobilize finance among farmers enabling them to invest in CSA practices. Also, the introduction of improved breeds in CSVs has benefited especially the larger livestock owners. However, the availability of credit is found to have mitigated the concentration of improved livestock ownership since the diffusion of improved livestock in CSVs was somewhat more equitable than the (spontaneous) spill-over diffusion in the non-CSVs (reducing the Gini by 0.04).

Keywords Climate-smart agriculture · Adoption · Inequality · Finance

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1 Introduction

Climate change and variability pose a major risk to smallholder farmers given that their economic activities are climate-sensitive. Climate-smart agriculture (CSA) is an approach that helps transform agri-food systems toward green and climate-resilient practices. It relates to actions both on-farm and beyond the farm and incorporates technologies, policies, institutions, and investments (Wakweya 2023). It aims to simultaneously make smallholder farmers more resilient as well as enhance agricultural productivity (Lipper et al 2014). In the wake of climate change and variability, there is a need for farmers to adopt and diffuse CSA practices. CSA is not a universally applied practice but rather a tailored adoption of one or more practices to local production circumstances. Evidence shows that the adoption of locally adapted CSA portfolios can increase productivity by 7 to 18% (Porter et al. 2014; Challinor et al. 2014). Yet adoption and diffusion rates of CSA practices are low, despite their potential to increase resilience and agricultural productivity (Branca et al. 2011; Makate 2019).

By and large, for a wide range of CSA practices, adoption usually requires some form of upfront investment in short-term inputs, such as fertilizers and seeds, and long-term investments in fixed inputs such as equipment, which are a significant barrier to adoption (Gikonyo et al 2022; Teklu et al 2023). In case savings are inadequate or allocated for other household expenditures in the future, such as school fees, smallholders have to resort to credit to meet their liquid financial needs (Simtowe and Zeller 2006). Access to credit (and land titles as collateral) therefor can have a positive impact on CSA adoption (Agbenyo et al. 2022; Tanti et al 2022; Teklu et al 2023; Yiridomoh et al 2022). Credit market failure is a frequently cited reason for low adoption rates (Carter 1989; Makate et al. 2019; Ogada et al. 2014). The small number of banks in rural areas and high transaction cost of formal credit and stringent credit conditions (e.g., land as collateral, repayment period, and interest rates) make it hard for farmers to access credit (Odoemenem et al. 2005). Although opportunities for mobile banking have increased recently, they often do not address the needs of smallholders.

Given this body of evidence that cites credit constraints for adoption in general, smallholders are likely also facing the challenge of inadequate funds to invest in CSA practices. For this reason, the climate-smart village (CSV) approach was introduced by the Consultative Group on International Agricultural Research (CGIAR) in their Research Program on Climate Change, Agriculture and Food Security (CCAFS). It included interventions both directly supporting the adoption of CSA practices and indirectly through supporting the mobilization of financial resources within community-based organizations (CBOs), among many others. Climate and agricultural development finance form a key component of the CSV approach, next to CSA practices and technologies (Aggarwal et al 2018). However, while earlier research has shown that the CSV approach leads to higher CSA adoption rates (e.g., Ogada et al. 2020), much less is known whether the CSV approach actually improves access to savings and credit and whether this has affected CSA investments.

Also, it is a well-known concern that agricultural innovations do not always benefit all farmers but can be biased toward better-off segments. This is because poorer farmers have more stringent limitations of resources and risk-taking capability (Opola et al. 2021). The CSV approach—including its savings and credit component—builds on local social capital, through the CBOs and their member groups, with a high degree of women membership, and the potential to reach poorer farmers. For example, Pamuk et al. (2022) estimated a positive effect on the adoption rates of several CSA practices for farmers receiving

microfinance services (and trainings) from CBOs, and this effect became more pronounced for households with higher scores on women empowerment. As the inclusion of CBOs is a key element in intervention models that promote the inclusiveness of agricultural innovations (Hoffecker 2021; Pamuk et al 2022), we could expect a positive effect on the distributional patterns of CSA adoption. However, the previous literature has paid little attention to the distributional impact of the CSV approach and improved access to savings and credit.

This paper makes the following contributions to the literature on CSA adoption. First, we estimate the impact of the CSV intervention on the adoption of improved livestock with enhanced production performance vis-à-vis indigenous breeds in the Nyando Basin, western Kenya. While most CSA studies target crop production, the current study complements these by focusing on the adoption of improved livestock breeds. Improved goats and sheep are seen as one of the most promising forms of CSA in the area of the Nyando Basin to increase food security where farms are small, soil erosion severe, and indigenous livestock maladapted to climate change manifested through increasingly frequent droughts, floods, and variable rainfall (Ojango et al. 2016). Second, we study the impact of the CSV intervention on credit and savings access, organized through CBO groups, and how this affects the adoption of improved livestock breeds, complementing the existing literature on the role of credit for agricultural adoption. Third, we also analyze the distributional impacts of the CSV intervention using censored quantile regressions and investigate whether the availability of credit in this way has mitigated the highly inequitable ownership distribution of improved breeds which can be observed in our research area. This distributional analysis provides an ex-post indication of the (intended) inclusiveness of the CSV interventions and complements the literature on the inclusiveness of agricultural innovations (Opola et al. 2021; Hoffecker 2021; Alia et al. 2018).

The remainder of the paper is organized as follows. We start by presenting the study context, data, and empirical strategy. Next, the results of the study are presented in terms of effects on adoption and distribution. The last section includes the main conclusions and policy implications.

2 Materials and methods

2.1 Study context

This study builds on the 2017–2021 NWO-CCAFS research project “Climate-Smart Financial Diaries for Scaling in the Nyando Basin, Kenya” which in turn builds on the CCAFS activities starting in 2011 targeting smallholders in the lower Nyando Basin in western Kenya which were implemented as part of its CSV approach (Lipper et al. 2014). The lower Nyando Basin study site is located in the plains of Lake Victoria in Kisumu and Kericho counties and comprises a 10 km by 10 km block. Kericho is characterized by a higher altitude and a higher annual rainfall than Kisumu, although the length of the growing period is equal for both (Sijmons et al. 2013). The research area is a typical case for many African countries, including severe problems of agricultural stagnation, environmental degradation, and deepening poverty, aggravated by climate change causing more erratic rainfall patterns and shortening of growing season (Ndiritu 2021). One of the most promising avenues for CSA in the area is drought-resistant livestock breeds.

Livestock breeding was the CCAFS entry point in sheep and goats upgrading intervention strategy to improve the adaptability of local breeds to climate change and variability.

Traditionally, sheep and goats tend to graze on the harvest residues and suffer a scarcity of feed during the dry periods. As is well known, small ruminants are the dominant live-stock kept by small and female farmers because of the low costs of acquiring and maintaining when compared to cattle (Ojango et al. 2016). Through the International Livestock Research Institute (ILRI), more resilient Red Maasai sheep and Galla goats were introduced to be crossbred with indigenous breeds (70 breeding Galla goats were introduced in 2012, followed by 30 breeding Red Maasai sheep in mid-2013). The Red Maasai sheep is more drought-resistant and mostly immune to parasites and has enhanced production performance vis-à-vis indigenous breeds. Additionally, Galla goats are more suited under harsh conditions than indigenous goats, while having better milk and meat production traits (Ojango et al. 2016). We note that both breeds are indigenous to Kenya, and hence, ample experience has been gained with these animals by Kenyan farmers outside the Nyando Basin. During the introduction period, the improved breed animals were donated and distributed by the three CBOs to demo farms leading farmers in the CSVs to be crossbred and diffused among their communities. It was projected that the Red Maasai sheep and Galla goat crosses introduced by ILRI would replace the indigenous breeds fully in all CSVs by 2018 (Radeny et al. 2018). The market price of improved young stock amounted to approximately 70 US\$ and 100 US\$ per Red Maasai sheep and Galla goat respectively compared to 35 US\$ for indigenous breeds (Bonilla-Findji et al. 2017; Wattel et al. 2018). In more recent years, also, improved varieties of indigenous chickens (mainly Kenbro) were introduced by KALRO in the CSVs (through a partnership with ILRI). These improved free-range dual-purpose chicken breeds have higher productivity than the indigenous Kienyeji village breeds (starting egg production earlier and growing faster if bred for slaughter) and are more disease-resistant. The introduction of improved breeds was aligned with trainings by ILRI to improve livestock management of rearing, grazing, supplementary feeding, controlled mating, and livestock health practices.

CCAFS organized in 2011 participatory community meetings in 7 randomly selected villages in a 10 km×10 km block comprising 106 villages in total. Farmers in the selected villages were advised to form CCAFS-related CBOs with a focus on dealing with climate change challenges by improving their agriculture through CSA practices. These CBOs formed umbrella organizations of subgroups, many of which already existed but were disjoint and not necessarily focusing on improving farming through the improved CSA practices. Subsequently, CCAFS organized its activities through these CBOs, and all members who joined participated in CCAFS activities from 2011 onward. Over time the communities in the research area have organized themselves into three CBOs which are made up of 58 self-help groups from the 106 villages (CCAFS continued to operate only in the 7 initially selected villages). These three CBOs enrolled approximately 2500 households, and women account for 80% of the members. The CBOs are legal entities, registered with the county governments. The communities also use the CBO groups to pool financial resources which have increased substantially over the research period to provide credit for on-farm (CSA) investment, as well as for other purposes (Branca et al. 2011; Radeny et al. 2018; Wattel et al. 2018). Not all members of the CBO groups did participate in a community savings and loan group, however.

2.2 Data and descriptive statistics

For this study, we use data that was collected as part of the CCAFS activities as well as the NWO-CCAFS project. We acknowledge upfront that the sample size used is relatively small, and we therefore consider this paper to be a case study, highlighting the lessons

Table 1 Number of households in 2017–2019–2020 surveys

	2017	2019	2020
Survey sample			
CSVs	180	88	85
Non-CSVs	216	34	33
Total	396	122	118
Balanced panel sample			
CSVs	85	85	85
Non-CSVs	33	33	33
Total	118	118	118

learned from the specific intervention for scaling of the intervention. Having said this, we still feel that the data are rich enough to support a formal statistical analysis and include dedicated tests to ensure unbiasedness and generalizability of our results. Specifically, we use three waves of a farm household survey conducted in 2017, 2019, and 2020 respectively (Table 1). The 2017 survey selected a random sample from the farm households that were monitored in 2015 by CCAFS as part of their monitoring and evaluation (M&E) activities. This 2017 CCAFS Evaluation Survey consists of two subsamples: one for the CSVs (“participating households”) and one for the non-CSV (“non-participating households”). Monitored households were members of CBOs and participated in CCAFS activities (which were organized through these CBOs). All CSV households are residing in villages located 10 km×10 km from which the CSVs were randomly selected in 2011 at the start of the CCAFS project. The sample of non-CSV households is a random sample of households who resided in villages outside the 10 km×10 km grid. Villages were identified that were very similar to the CSVs in terms of observable biophysical characteristics (i.e., temperature, precipitation, soil type, and landscape) and socio-economic characteristics (i.e., most prevalent farming system, main agricultural crops, and livestock ownership). Households from these villages were then listed with the help of the local administrator to provide a sampling frame for the non-CSVs. A random sample was then made from this sampling frame.

The total number of households included in the CCAFS Evaluation Survey equals 433 (Ogada et al. 2020; Radeny et al. 2018), but we focus on only the 396 households located in the same villages covered by the 2019 and 2020 surveys. Not all villages were included in the 2019 and 2020 surveys for logistical reasons. The 2019 and 2020 survey samples form a (stratified) random subsample from the 2017 sample, and therefore, the 2017–2019–2020 surveys are comparable over time (using sampling weights for 2019 and 2020). Ultimately, the balanced panel sample comprises 118 farmers. Table 1 reports the number of households that were sampled in each of the surveys, across CSVs and non-CSVs, as well as in the balanced panel sample.

In the remainder of this paper, we will focus primarily on the balanced panel of 118 households for two reasons. First, we are interested in changes in adoption over time, and therefore, we would like to avoid unnecessary sampling variation also considering the relatively small sample sizes as reported in Table 1. Second, while the impact of the CCAFS intervention will be identified on the basis of cross-sectional variation for lack of a pre-treatment baseline,¹ our analysis of the role of credit for the adoption of improved livestock

¹ The assignment of the climate-smart villages under the CCAFS intervention took place in 2011; the survey period on the outcome variables of interest runs from 2012 to 2020 (including recall data).

breeds relies on time variation in the data requiring panel data.² However, the relatively large cross-section sample for 2017 will be exploited to verify whether our results are robust to using a significantly larger sample and alternative estimation technique.³

2.3 Empirical strategy

2.3.1 Impacts of CSV interventions

The first step in the empirical analysis is to estimate the impact of the CSV interventions on the adoption of CSA practices and access and use of credit/savings. Suppose we estimate:

$$y_{ivt} = \alpha_t + \beta \text{CSV}_{iv} + \varepsilon_{ivt} \quad (1)$$

where subscripts i , v , and t indicate the farm household, village, and year respectively. The dependent variable y_{ivt} is a binary indicator of, respectively, adoption of improved livestock (sheep, goats, and chicken), improved ruminants (sheep and goats), membership of savings/credit group (i.e., access), credit use (for any purpose, agriculture or CSA), savings use, and presence of credit constraints. The intercept α_t is allowed to vary across time, and CSV_{iv} is a dummy variable which is time-invariant as villages were either assigned as CSV or non-CSV throughout the survey period (and no households moved).⁴ The error terms ε_{ivt} are clustered at the village level.

Estimation of Eq. (1) assumes that the assignment of the CSVs is as good as random. The CSVs were randomly selected within a 10 km×10 km block. The control villages were selected from outside the 10 km×10 km block to avoid spill-over effects but were purposefully selected to be very similar to the CSVs in terms of observable biophysical and socio-economic characteristics. The question remains, naturally, whether the control villages are indeed similar and therefore whether the assignment of CSVs can be considered as random conditional on all relevant factors.

Balancing tests provide evidence that the control and treatment villages are indeed similar with respect to various village characteristics (Table 2). Although CCAFS implemented a baseline survey in 2011, this covered only the treatment villages. Therefore, the presented village characteristics are from the 2017–2019–2020 surveys. To avoid endogeneity bias, only (plausibly) time-invariant characteristics are presented. When the same characteristic has been reported in multiple waves, information from the earliest available wave is presented. Characteristics of the control and treatment villages are similar except for distance to food markets (at 10% significance). However, the joint test on significance has a p -value of only 0.47. Unfortunately, we do not have data on other village characteristics, but based on the available characteristics, we do not find that the control and treatment villages are systematically different with respect to these observed characteristics. We acknowledge that there may be systematic and relevant differences in terms of unobservable village characteristics, but given the large diversity of variables included in the balancing test, we proceed under the (untestable) assumption that our dataset would have picked up on such differences.

² Through the use of lags and exploiting within-household variation in credit access (household fixed effects).

³ Specifically propensity score matching which is not feasible when using the balanced panel because of its small sample size.

⁴ The assignment of the climate-smart villages under the CCAFS intervention took place in 2011; the survey period runs from 2012 to 2020.

Table 2 Balancing tests on village and household characteristics

	Non-CSV	CSV	Diff	<i>p</i> -value
Village characteristics				
Located in Kericho county (dummy, Kericho = 1)	0.41	0.43	−0.02	0.88
Distance to motorable road (log, km)	−1.25	−1.61	0.36	0.40
Distance to food market (log, km)	1.03	0.34	0.69	0.08*
Distance to livestock market (log, km)	2.01	2.01	−0.00	0.99
Altitude (m)	1283.6	1289.0	−5.33	0.87
<i>F</i> -test on joint significance (<i>p</i> -value)				0.47
Household characteristics				
Household size	5.54	6.09	−0.55	0.02**
Gender of household head (dummy, male = 1)	0.72	0.71	0.00	0.96
Age of household head (years)	49.8	52.1	−2.29	0.14
Education of household head (levels 1–7)	3.21	3.14	0.07	0.66
Ethnicity of household (dummy, Luo = 1)	0.81	0.69	0.12	0.01**
Number of cattle owned before 2012	3.05	3.77	−0.72	0.13
Number of sheep owned before 2012	2.73	2.62	0.11	0.90
Number of goats owned before 2012	1.93	3.69	−1.76	<0.01***
Membership of groups before 2012 (fraction)	0.14	0.36	−0.22	<0.01***
<i>F</i> -test on joint significance (<i>p</i> -value)				<0.01***

The figures are weighted with sampling weights. Standard errors are robust

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

Not all farmers in the CSVs have participated in the CCAFS interventions, i.e., becoming a member of a CCAFS-supported CBO. Specifically, farmers who have chosen to participate in CCAFS activities in CSVs may differ systematically from farmers who have chosen not to participate leading to possible confounders. In Table 2, we therefore also compare the control and treatment villages in terms of household characteristics. To avoid endogeneity bias, we limit ourselves to household characteristics that are (plausibly more or less) time-invariant or reported for the period before the CCAFS intervention started (i.e., 2011 or earlier). The households in the treatment villages do indeed differ significantly from the households in the control villages since they tend to have more members, more goats, more likely to be a group member, and less likely to be of Luo ethnicity. The joint test on significance confirms that the treatment and control households are different ($p < 0.01$).

A standard approach to estimating treatment effects in a setting where households can self-select into a randomly allocated treatment is to use instrumental variables, where the random treatment allocation is used as an instrument for the actual uptake of the treatment. In our case, the treatment (and IV) is whether a household is in a CSV, while the uptake is given by whether a household chooses to participate in a CCAFS-supported CBO:

$$y_{ivt} = \alpha_t + \beta \text{CCAFS}_{iv} + \varepsilon_{ivt} \quad (2)$$

where CCAFS_{iv} is a dummy indicating whether a household is participating in a CCAFS-supported CBO. The CCAFS dummy is time-invariant as households decided to participate at the beginning of the intervention and no households dropped out subsequently (no

attrition). IV estimation of Eq. (2) will give the local average treatment effect (LATE) on various CSA outcome variables y_{ivt} . Within an IV framework, the treatment effect is called “local” because it is estimated for the subset of households which are actually taking up the treatment (the so-called “compliers”) excluding the “always-takers.” In case of one-sided non-compliance, LATE equals average treatment effect on the treated (ATT) effect, which is the case here as no households in non-CSVs did (and could) participate in CCAFS interventions (i.e., absence of always-takers).

Due to the survey sampling design, we have the complication that the 2017–2019–2020 surveys do not include the households in the CSVs which chose not to join the CCAFS-supported CBOs.⁵ Given that uptake (CCAFS_{iv}) is likely affected by unobservable factors that are correlated with the error terms in (1) and (2), it is not possible to estimate the ITT effects of the CSV interventions using Eq. (1) and the ATT with Eq. (2).

However, given the sampling design, we can still estimate the ATT by estimating Eq. (1) provided we also (flexibly) control for the household selection effects into treatment (control function approach). Assume that participation can be modeled as

$$\begin{aligned} \text{CCAFS}_{iv}^* &= \begin{cases} Z_{iv}\psi + \omega_{iv} & \text{CSV} = 1 \\ 0 & \text{CSV} = 0 \end{cases} \\ \text{CCAFS}_{iv} &= \begin{cases} 0 & \text{CCAFS}_{iv}^* \leq 0 \\ 1 & \text{CCAFS}_{iv}^* > 0 \end{cases} \end{aligned} \quad (3)$$

where CCAFS_{iv}^{*} is a latent variable and Z_{iv} are household and village factors affecting participation (including possibly a constant). Given that households in climate-smart villages are only observed if they do participate in a CCAFS-supported CBO and omit subscripts, we have $E[\varepsilon | \text{CSV} = 1] = E[\varepsilon | \text{CCAFS}_{iv}^* > 0] = E[\varepsilon | \omega > -Z\psi] = f(Z\psi)$. Because there is no selection issue in the control villages, we also have $E[\varepsilon | \text{CSV} = 0] = 0$. Hence, we can estimate the ATT with Eq. (4)⁶:

$$y_{ivt} = \alpha_t + \beta^{ATT} \text{CSV}_{iv} + h(Z_{iv}\psi) + \varepsilon_{ivt} \quad (4)$$

where h is the control function defined by $h(Z\psi) \equiv f(Z\psi)$ if $\text{CSV} = 1$, zero otherwise. Also, control variables can be included in Eq. (4) apart from those that are controlling for household and village factors affecting the participation in the CCAFS-supported CBOs. This is not necessary to consistently estimate the ATT effect, however, given that the assignment of CSV is as good as random (but it could increase precision).

We will use Eq. (4) to estimate the impact of the climate-smart village intervention on adoption using the balanced panel of 118 households and approximating the control function with a piecewise linear function. An alternative estimation strategy is to use propensity score matching (PSM), but this requires a larger sample. We can use the cross-section sample of 396 households from the 2017 survey to test whether the estimated ATTs from Eq. (4) using the balanced sample are robust to using a significantly larger sample and alternative estimation technique (PSM). For the PSM, the household controls listed in Table 2 are used as the pre-treatment selection variables, and the Epanechnikov kernel is used to match treatment with control households.

⁵ Recall that all CCAFS interventions were channeled through CBOs.

⁶ We note that we can also estimate the equation $y_{ivt} = \alpha_t + \beta^{ATT} \text{CCAFS}_{iv} + h(Z_{iv}\psi) + \varepsilon_{ivt}$ because $\text{CCAFS}_{iv} = \text{CSV}_{iv}$ due to the sampling design. This equivalence also shows that estimation of Eq. (4) gives the ATT rather than ITT.

To estimate the impact of the CSV intervention, a linear probability model (LPM) was used. LPM is appropriate as it yields consistent estimates (Greene 2000) and is standardly used in impact assessments. LPMs (and OLS) are also far more tractable and flexible in the handling of unobserved heterogeneity (Janvry et al. 2006). Furthermore, LPMs do not need to assume a distribution for the error terms unlike limited dependent variable models such as logit or probit. Also, Angrist and Pischke (2009) have shown that in practice the marginal effects estimated with LPMs are typically quite similar to those derived from nonlinear probability models. While it is true that the main disadvantage of the LPM is that its predictions may not fall within the 0–1 interval, it is the marginal effects that we are interested in.

2.3.2 Heterogeneity in impact

We will consider also two sources of impact heterogeneity. First, the CCAFS interventions ran over several years, and therefore, we want to allow for differences in impact over time, reflecting possible differences in treatment intensity over time as well as lagged and/or cumulative effects. Hence, we may allow β^{ATT} to vary across years by including interactions of the CSV dummy with time dummies (β_t^{ATT}). Second, given that CCAFS activities were tailored to the needs of individual farmers, β^{ATT} may also be allowed to vary across types of farmers, and we will allow for this by including interaction terms of the CSV dummy with farm household characteristics in Eq. (4).

2.3.3 Role of access to savings and credit

Estimation of the ATT with Eq. (4) will show the impact of the CSV intervention that was implemented in 2011 on various CSA outcome variables y_{it} over the period 2012–2020, including improved access to savings and credit through membership in a savings and loan group subsequently. In case a significant impact is found for access to finance, an important question is whether this was instrumental in changing the other CSA outcomes, especially the adoption of improved ruminants (goats and sheep). The climate-smart village approach is an integrative strategy for scaling up adaptation options in agriculture, and access to finance is only one component of this broad framework (Aggarwal et al. 2018). However, increased access to finance is seen as a key mediator (M) through which farmers will be able to adopt climate-smart agriculture, c.q., improved ruminants in the Nyando Basin in Kenya (Fig. 1).

where $t = 2012, 2016, 2017, 2019, 2020$. Recently, causal mediation analysis has been developed attempting to estimate the importance of mediators in explaining the total average causal effects identified in (quasi-)experiments, by decomposing the total effect into an indirect effect mediated by improved access to finance and a direct effect reflecting all other mechanisms. It has been shown that this is only possible under the assumptions of sequential ignorability, which are quite strong because of the plausible presence of unobserved

Fig. 1 Causal diagram with access to finance as mediator

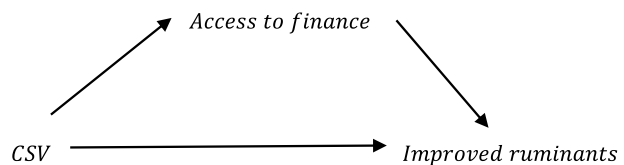
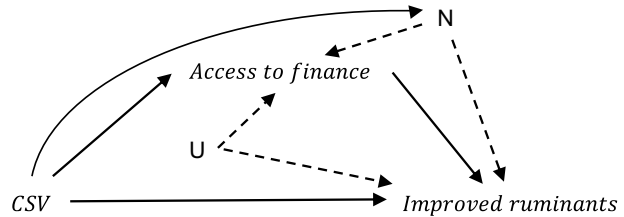


Fig. 2 Pre-treatment (U) and post-treatment (N) confounders



pre-treatment (U) as well as observed and unobserved post-treatment confounders (N) (Imai and Ratkovic 2013, Carpena and Zia 2020)⁷ (Fig. 2).

The presence of pre-treatment confounders U, such as *ex-ante* risk aversion or time preferences, can be addressed by (quasi-)experimental methods and/or the inclusion of control variables allowing for the identification of total average causal effects. The key challenge for causal mediation analysis is the presence of *post-treatment* confounders N, however, as controlling for such confounders is insufficient to identify the contribution of the mediator in the total causal effect. For instance, assume that the climate-smart village intervention impacts *ex-post* risk aversion (N) by making farmers less risk averse. Further suppose that as a result of this lower risk aversion, farmers are more willing to join savings and loans groups ($N \rightarrow M$) and to adopt CSA practices, including improved livestock breeds ($N \rightarrow Y$). Even if we can control for *ex-post* risk aversion, this confounding will make it impossible to estimate how much of the adoption of improved ruminants is due to improved access to finance (Carpena and Zia 2020).⁸

Because we think that the sequential ignorability assumptions are highly unlikely to hold in our case, we address a less ambitious but still very (policy-)relevant question: “to what extent does improved access to finance affect the adoption of improved ruminants within climate- and non-climate-smart villages?” In order to address this question, we estimate the following equation:

$$\text{Improved ruminants}_{ivt} = \alpha_t + \beta \text{CSV}_{iv} + \delta \text{CreditAccess}_{ivt} + h(Z_{iv}, \psi) + FE_t + \epsilon_{ivt} \quad (5)$$

where $\text{Improved ruminants}_{ivt}$ and $\text{CreditAccess}_{ivt}$ are dummy variables capturing respectively whether the farm household has improved ruminants and is a member of a savings and loan group. The key variable of interest is δ showing the impact of improved access to finance on the adoption of improved ruminants. In Eq. (5) the control function $h(Z_{iv}, \psi)$ is again included to control for the household selection effects in treatment.⁹ To control for possible pre-treatment (U) and post-treatment (N) confounders, we can now exploit the panel dimension of the data by including household fixed effects.¹⁰ While we acknowledge

⁷ In the literature, also, other assumptions have been introduced such as the sequential g-estimation, but this requires an equally strong “no-interaction” assumption to derive the average indirect effect (Carpena and Zia 2020).

⁸ Technically, the second of the sequential ignorability assumptions is violated as M should be ignorable given only the treatment (c.q., CSV) and baseline covariates.

⁹ The sample selectivity effect (S) has been omitted from Figures 1 and 2 to avoid cluttering but would imply arrows “CSV \rightarrow S”, “Access to finance \rightarrow S” and “Other CSA outcomes \rightarrow S” (see Bareinboim, et al. 2014). Include in references: Bareinboim, E., Tian, J., & Pearl, J. (2014, June). Recovering from selection bias in causal and statistical inference. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 28, No. 1).

¹⁰ We note that with household fixed effects, β and the control function term $h(Z_{iv}, \psi)$ are no longer identified. Also, because the CSV intervention started in 2011 before the survey period, the fixed effects capture both (unobserved) pre- and post-treatment time-invariant factors.

that it cannot be ruled out that the results are still confounded, robust findings for the estimated key parameter δ against using control functions and household fixed effects should alleviate some of these endogeneity concerns.

If we find that both the climate-smart village intervention has improved access to finance (from Eq. (4)) and access to finance has increased the adoption of improved ruminants (from Eq. (5)), this suggests that access to finance is indeed a mechanism through which the climate-smart intervention has increased CSA adoption. A popular method to support the idea that access to finance is an especially important mechanism within an intervention is to include an interaction term $\text{CreditAccess}_{ivt} \times \text{CSV}_{iv}$ in (5). A positive effect from this interaction term can be seen as supportive of the importance of access to finance as a mediator. We note that this provides still only suggestive evidence if the sequential ignorability assumptions are unlikely holding (Carpena and Zia 2020).

2.3.4 Impact on improved livestock ownership distribution

The last step of the empirical analysis will look at the distributional effects of the CSV interventions on the adoption of improved ruminants. A very high inequality in improved livestock ownership may reflect a process where early adopters take advantage of the new technology while other adopters are following later. In that case, inequality will be high initially but fall over time as more and more farmers are switching from indigenous to improved breeds. Alternatively, a highly skewed distribution of improved livestock may also reflect structural constraints to the adoption of improved breeds, however, such as lack of knowledge, availability of and access to pure-bred animals and/or veterinarian services, and credit constraints. In the latter case, inequality in improved livestock ownership is expected to remain high and higher than for indigenous breeds.

The CSV intervention aimed at distributing the benefits of improved breed adoption equitably by providing training and veterinary services as well as by introducing pure-bred sheep and goats for crossbreeding, reducing both the costs and the need for special knowledge. Moreover, by supporting savings and credit associations, which include a large proportion of female and poorer farmers, the intervention may have supported the adoption of improved breeds by relaxing credit constraints for these vulnerable farmers. One possibility is to estimate the effect of CSV and credit access with a Poisson regression or one of its generalizations (negative binomial, generalized negative binomial). However, this approach has several disadvantages. First, one needs to make (strong) distributional assumptions that may not hold in practice. Second, we found that the predicted distribution using a Poisson regression (or one of its generalizations) poorly matches the actual distribution for our data. And third, because of its exponential functional form, there is no estimated distributional impact from the CSV intervention or credit access. Of course, one could include interaction terms of the CSV and/or credit access dummy with other variables in the model, to generate an estimated impact on inequality, but it is not clear which interaction terms should be included.

We therefore opt for a more flexible approach, estimating for each observation (i.e., household) the 10th, 20th, 30th, ..., 90th percentile using censored quantile regression, with left-censoring at zero (Chernozhukov et al. 2015).

$$\hat{\alpha}_\tau, \hat{\beta}_\tau, \hat{\gamma}_\tau = \underset{\alpha, \beta, \gamma}{\operatorname{argmin}} \sum_{i=1}^N \left(\rho_\tau(y_{ivt} - \max(\alpha + \beta \text{CSV}_v + X_{ivt}\gamma, 0)) \right) \tau = 10, 20, 30, \dots, 90 \quad (6)$$

with ρ_τ as the check loss function, y_{ivt} as the number of improved small ruminants (goats/sheep) owned by farm household i in village v and year t , and $X_{ivt}\gamma$ as village

and household-level control variables. In order to test whether the availability of credit (through a savings and loan group) has mitigated against the highly inequitable ownership distribution of improved breeds, Eq. (6) will also be estimated including the variable $\text{CreditAccess}_{it-1}$. Because censored quantile regression does not allow for the inclusion of (household) fixed effects, we include a one-period lag to alleviate potential endogeneity concerns. We already note, however, that the estimates from Eq. (5) suggest that omitting household fixed effects does not appear to affect the estimates in any significant way (although we cannot rule out that this would be different for the censored quantile regression estimates).

Using the estimated censored regression coefficients, the different percentiles can be predicted for each household. Pooling the predicted percentiles across all households (using sampling weights) yields the predicted distribution of improved livestock ownership for the entire population. This predicted distribution can be compared with the actual distribution as a measure of goodness of fit. Finally, using the same estimated censored regression coefficients, the counterfactual distributions can be predicted for the case where the CSV and/or credit access dummies are set equal to zero. This will show whether the CSV intervention had a direct or indirect (through improved credit access) impact on the ownership distribution of improved livestock breeds.

3 Results

3.1 Descriptive statistics

The current number of indigenous and improved livestock (sheep, goats, and chickens) was elicited in each survey wave, as well as retrospective questions in the 2017 survey on livestock ownership in January 2016 and before the start of the CCAFS program in 2012. In the 2020 survey (Table 3), most households in CSVs raised chickens, followed by goats and sheep (95%, 70%, and 50% respectively). Those CSV households with livestock kept predominantly indigenous breeds. The adoption rates of improved breeds as of 2020 are in CSVs 11% for sheep and 25% for goats, implying that the projected universal adoption of improved sheep and goat breeds has not been achieved yet. In 2020, CSV households are much more likely to keep improved breeds of sheep ($p=0.03$) and goats ($p=0.05$) than non-CSV households, providing *prima facie* evidence of the effect from the CCAFS interventions. The adoption rate of improved chickens as of 2020 is 9% (and does not statistically differ between CSV and non-CSV households which does not come as a surprise since it was not within the initial scope and attention of CCAFS intervention).

Figure 3 shows the distributions of indigenous and improved sheep and goat ownership in 2020. While it is clear that indigenous livestock ownership is highly unequal with a Gini coefficient of 0.59, this is not necessarily surprising as livestock is only one of the many livelihood options available to the farmers. What is remarkable, however, is that the distribution of improved livestock ownership is far more unequal with a Gini coefficient of 0.93. This suggests that the introduction of improved breeds has not benefited all livestock owners equally resulting in a highly concentrated adoption pattern. One may argue that this is actually not surprising, given that it involves a new technology which is adopted first by early adopters before it becomes a mainstream technology (Rogers 2003).

The surveys provide information on savings and credit access, use, and constraints. Table 4 reports descriptive information on savings and credit access, use, and

Table 3 Descriptive statistics improved livestock breeds adoption

	CSV					Non-CSV				
	2012	2016	2017	2019	2020	2012	2016	2017	2019	2020
Sheep										
Household has sheep (%)	42	50	52	49	50	20	24	33	35	42
Household has indigenous sheep (%)	38	43	45	36	44	21	25	32	35	39
Number of indigenous sheep if any (#)	5.45	5.12	4.82	4.62	3.78	6.16	6.8	5.67	5.31	4.07
Household has improved sheep (%)	6	11	12	13	11	1	1	1	0	3
Number of improved sheep if any (#)	8.62	8.24	7.21	6.6	7.26	1	3	4.5	–	12.09
Goats										
Household has goats (%)	60	67	68	76	70	37	48	57	70	72
Household has indigenous goats (%)	46	50	51	52	55	38	48	55	65	66
Number of indigenous goats if any (#)	7.26	6.68	6.81	4.86	4.16	6.53	6.18	6.4	5.06	4.52
Household has improved goats (%)	20	24	24	24	25	2	3	3	5	7
Number of improved goats if any (#)	5.77	6.22	6.84	6.89	6.19	1.3	4.29	7.57	2.58	9.07
Chickens										
Household has chickens (%)	75	80	77	86	95	64	73	73	81	97
Household has indigenous chickens (%)	69	73	71	81	90	68	77	73	81	90
Number of indigenous chickens if any (#)	18.73	13.52	11.87	15.35	11.26	10.77	13.49	10.43	16.91	11.88
Household has improved chickens (%)	6	8	8	5	9	1	1	1	0	8
Number of improved chickens if any (#)	14.88	20.52	19.48	12.29	13.31	3	3	1	–	24.65

The figures are weighted with sampling weights

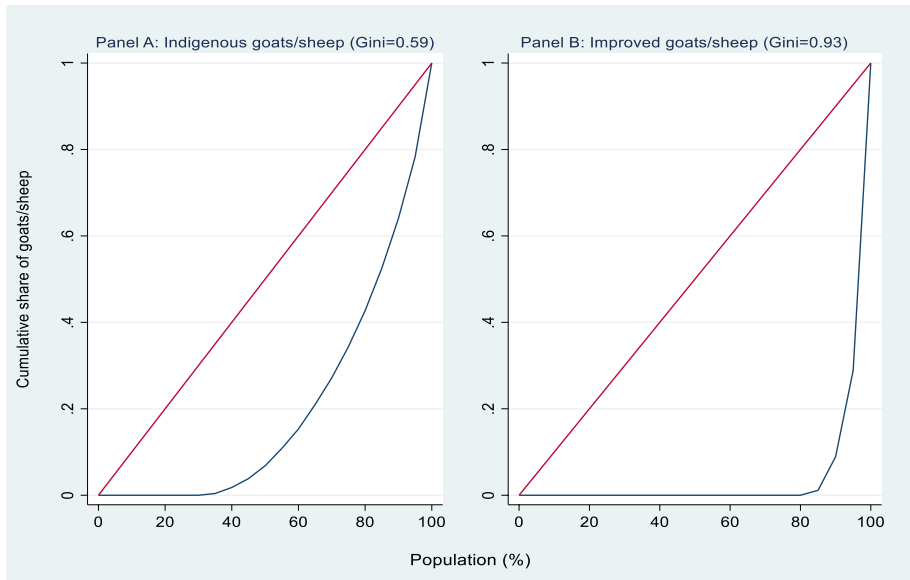


Fig. 3 The Lorenz curves of indigenous and improved sheep and goats

constraints. Savings and credit access is based on membership or not in a community savings and loan group.¹¹ The use of savings and credit was directly ascertained. Whether the availability of the credit has been rationed is elicited by asking whether anyone in the household tried to obtain credit but was refused or did not receive the entire amount (i.e., insufficient credit provision for the smallholders' needs). This quantity constraint approach is thus a supply-side credit restriction. We do not count as credit-constrained those smallholders who chose not to take up (larger amounts of) credit as a result of high transaction costs or risk aversion (i.e., transaction cost and risk rationing). Because of changes in questionnaires over time, not all information is available across the years.

The information for the pre-survey years (i.e., before 2017) is based on recall questions addressing the financial circumstances in the previous year (2016), as well as the first year after introducing the improved breeds in the area (2012).

The majority of the smallholders joined a community savings and loan group (usually organized within a CBO) over time and many saved. About half of the smallholders used credit at the time of the survey in 2020 (52% in CSVs and 43% in non-CSVs), while only a small percentage of the smallholders are using credit for agricultural investments in general (6–15%), or to finance CSA more specifically (6–12%). The probability of being credit-constrained did not differ significantly between the years under study as reported by the smallholders (ranging from 7 to 14%). The average amount of savings deposited in 2020 was 126–134 US\$. The average credit uptake was higher at 144–205 US\$ in 2020.

¹¹ As discussed in Sect. 2.1, not all farmers in CSVs have participated in CCAFS-supported CBOs, and not all members of these CBOs participated in a community savings and loan group.

Table 4 Descriptive statistics of savings and credit access, use, and constraints

	CSV					Non-CSV				
	2012	2016	2017	2019	2020	2012	2016	2017	2019	2020
Savings and credit access (membership) (%)	35	66	70	80	80	9	49	49	72	72
Use of savings (%)	–	–	–	64	79	–	–	–	51	86
Use of credit (%)	38	–	50	62	52	23	–	44	40	43
Use of credit for agriculture (%)	24	–	5	19	15	22	–	5	13	6
Credit for CSA (%)	–	–	–	18	12	–	–	–	9	6
Credit-constrained (%)	–	9	9	14	9	–	9	9	7	11
Average savings amount (US\$)	–	–	–	97	126	–	–	–	65	134
Average credit amount (US\$)	–	–	101	119	144	–	–	42	94	205

The figures are weighted with sampling weights

3.2 Impacts of CSV intervention on adoption of improved breeds and access, use, and constraints to credit/savings

Table 5 shows the treatment effects (on the treated) of the CSV intervention (i.e., Eq. (4)) on the following dummy outcomes respectively: improved livestock (sheep/goats/chicken), improved sheep and goats, membership of savings and credit group (as a proxy for access), credit use, credit use for agriculture, credit use for CSA, savings use, and credit constraints. The number of observations varies across outcomes because the information was not always elicited throughout the survey waves for all outcomes.¹² Panel A shows the results if no village and household controls are included. The equation is estimated with ordinary least squares, and standard errors are clustered by village. Columns (1) and (2) show that farmers participating in CCAFS activities in CSVs have a 35% point higher probability of having improved breeds due to the intervention ($p < 0.01$). Approximately, 25% of the variance was explained with these models. Correlations between village and household characteristics are generally low, also among the three distance variables (Table 9 in Appendix 1). Adoption of improved breeds increased till 2017 but not anymore afterward (see the time dummies in columns (1) and (2) in Table 10 in Appendix 1). The CSV interventions increased the membership of groups which have as key activity savings and credit (column (3)) by 20% point ($p < 0.05$). The interventions appear to also have increased the use of credit (overall, for agriculture, or for CSA). There is no effect of the CSV intervention on the probability of being credit-constrained (column (8)) or using savings (column (7)).

In panel B, we estimate Eq. (4) including the control function h to address potential selectivity. We approximate h with a piecewise linear function, i.e., $h(Z\psi) = Z\psi$ if $CSV = 1$, zero otherwise.¹³ As control variables, we have included the village and household characteristics listed in Table 4 (see Table 11 for additional estimation results). Comparing the estimates in panels A and B shows that the inclusion of the control function greatly reduces the precision of the estimates. However, the coefficients for improved livestock, improved sheep and goats, and savings and credit access remain positive and of similar magnitude (columns (1)–(3)).

In panel C (see Table 12 for additional estimation results), we add the control variables linearly to address selectivity and increase precision simultaneously. The results suggest that the main effects from the CSV intervention are in terms of adoption of improved livestock breeds and access to credit and savings (columns (1)–(3)).

Given that panels A–C in Table 5 are based on the relatively small balanced sample of 118 households, we also use the cross-section sample of 396 households from the 2017 survey to estimate the impacts of the climate-smart village intervention with propensity score matching (PSM). Panel D shows the estimated impacts, where we use the household controls listed in Table 2 as the pre-treatment selection variables and the Epanechnikov kernel to match treatment with control households (see Appendix 2 for the propensity score estimates and balancing tests).¹⁴ These estimates suggest, again, that the CSVs have a higher probability of having improved livestock, improved sheep and goats, and savings and credit access. The estimates for the other outcomes are less precise and lack

¹² Household non-response rates were very low, however.

¹³ We also tried a quadratic function, i.e., $h(Z\psi) = Z\psi + \lambda(Z\psi)^2$ if $CSV = 1$, zero otherwise, but this leads to overfitting (implausible estimates, convergence problems, mostly insignificant λ).

¹⁴ The village controls listed in Table 4 are from the 2019–2020 surveys and hence not available for all 396 households in the 2017 survey. This creates no problem, however, as the villages were randomly selected.

Table 5 Impacts of CSV intervention on adoption of improved breeds and access, use, and constraints to credit/savings

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit (dummy)	Use of credit culture (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Credit-constrained (dummy)
Panel A: no village and household controls, balanced panel 2012–2020 (OLS)							
CSV	0.35*** (0.07)	0.20*** (0.06)	0.17*** (0.06)	0.07* (0.04)	0.10*** (0.04)	0.01 (0.08)	-0.01 (0.03)
r^2	0.11	0.16	0.05	0.04	0.02	0.05	0.00
p	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
N	583	590	472	472	236	236	472
Panel B: with village and household controls, balanced panel 2012–2020 (piecewise linear control function, OLS)							
CSV	0.44 (0.39)	0.28 (0.30)	-0.14 (0.36)	-0.25 (0.24)	-0.66 (0.51)	1.13*** (0.37)	-0.37*** (0.12)
r^2	0.26	0.25	0.12	0.09	0.13	0.18	0.04
N	573	580	464	464	232	232	464
Panel C: with village and household controls, balanced panel 2012–2020 (OLS)							
CSV	0.29*** (0.05)	0.15** (0.06)	0.11 (0.07)	0.07 (0.04)	0.09 (0.06)	-0.01 (0.07)	-0.04 (0.03)
r^2	0.24	0.27	0.12	0.07	0.09	0.20	0.06
p	0.00	0.00	0.00	0.00	0.00	0.00	0.06
N	573	580	464	464	232	232	464
Panel D: cross-Sect. 2017 (PSM)							
CSV	0.24*** (0.04)	0.09* (0.04)	0.08 (0.06)	0.02 (0.03)			-0.02 (0.04)
N (on common support)	380	380	380	380			380

All regressions include year dummies. Standard errors are clustered by village and reported in parentheses, Additional estimation results for panels A–C are in Appendix 1 and for panel D in Appendix 2

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

significance.¹⁵ The combined results across the panels suggest that the climate-smart intervention has increased the adoption of improved livestock breeds as well as access to credit and savings (columns (1)–(3)).

3.2.1 Heterogeneity across time

The CCAFS interventions ran over several years, and therefore, one may want to allow for differences in impact over time, reflecting possible differences in treatment intensity over time as well as lagged and/or cumulative effects. We therefore allow β to vary across years, with the control variables included linearly (Appendix 3). The main finding from this analysis is that the impact of the CSV intervention on improved livestock shows an inverted U-shape, increasing till 2017 and declining afterward (columns (1) and (2)). The weakening impact of the CSV interventions cannot be attributed to a catching-up effect among the control villages as the year dummies do not show a clear increasing trend since 2017.

The impact of the intervention on membership of a group where savings and credit form a key activity is similarly declining over time (column (3)). However, the year dummies show an increasing trend in group membership also after 2017, suggesting that this component of the CSV intervention has been self-sustaining. For the other outcome variables, there is no clear time pattern, because the coefficients are imprecisely estimated and/or the pattern is non-monotonic (columns (4)–(8)).

3.2.2 Heterogeneity across wealth status and gender

As indicated earlier, an important question is whether the CSV approach is inclusive in an *ex-post* sense, i.e., when considering the impact rather than the design. Although the CSV intervention is designed to be inclusive—hence the focus on CBOs—there still can be unintended effects. First, the CCAFS activities were tailored to the needs of individual farmers, and hence, the treatment intensity may have differed systematically across types of farmers. It is also possible that more connected farmers still had better access to treatments. Second, even with equal treatment intensities across farmers, some types of farmers may have benefitted more.

In order to distinguish between types of farmers, we use the household balancing variables in Table 2 as they reflect baseline values and hence are unaffected by the intervention itself. We focus on two types of heterogeneity, in particular: namely, (initial) livestock ownership (as a wealth indicator) and gender of household head. We allow for heterogeneity in impacts by interacting the CSV dummy respectively with the quantiles of the total number of cattle, sheep, and goats owned by the households at baseline (Appendix 4) and the dummy for the gender of the household (Appendix 5). We note that the livestock ownership quantiles and household head gender dummy are also included as separate control variables.

The main findings from this more in-depth analysis are that the impact of the CSV intervention on improved breeds shows an inverted U-shape with ownership of livestock, suggesting that the biggest impact was felt by households in the 3rd quantile of the distribution (Appendix 4, columns (1) and (2)). The impact on being a member of a savings and credit group as well as the use of credit/savings is concentrated on the second quantile

¹⁵ No estimates are available for the outcomes credit for CSA and use of savings as this information was not asked in the 2017 survey.

(Appendix 4, columns (3)–(8)). This suggests that the intervention did improve credit/savings access but not so much for the poorest and the better-off.

Female- and male-headed households benefitted equally from the intervention (Appendix 5). Also, Table 4 shows that the intervention was balanced in terms of the gender of the household (i.e., no selection into treatment based on gender).

3.2.3 Effect of access to savings and credit adoption of improved breeds and use and constraints to credit/savings

The evidence points to improved access to finance for farmers in the climate-smart villages (Table 5, column (3)), although the impact is limited to the first 5 years after the start of the intervention because the market became saturated and membership stabilized in 2019 and 2020 at a level of 80% in CSVs (Table 4) and likely spill-over effects in non-CSVs. Given this impact, we can now address the empirical question to which extent improved access to finance over the period 2012–2017 has in turn affected the adoption of improved ruminants (goats and sheep). We can test this by estimating Eq. (5), and the results are reported in Table 6.

Membership in savings and credit groups increases the probability that farmers adopt improved ruminants by 0.17 in a regression without any village and household controls (column (1)). This result is robust to adding the village and household controls from Table 4, either in piecewise linear or linear form (columns (2) and (3)).¹⁶ In column (4), we exploit the panel dimension by including household fixed effects to control for possible (time-invariant) household-level confounders. Although this does not control for other, time-variant, confounders, the result is remarkably robust making it less likely that the estimate is driven by such omitted factors. Finally, in column (5), we estimate the impact of access to finance for the climate-smart villages and other villages separately—the result shows that the effect is only found in the climate-smart villages, suggesting that improved access to finance is indeed a key mechanism for the adoption of improved small ruminants within the climate-smart intervention.

3.2.4 Effect of CSV intervention and access to savings and credit on distribution of small ruminants

The foregoing analysis has shown that adoption of improved small ruminants was indeed higher in CSVs and among households who were members of a savings and loan group. The final step in our empirical analysis addresses the question of whether we can also observe an effect on the ownership distribution of improved livestock. Specifically, is it the case that the CSV intervention and availability of credit (through a savings and loan group) has mitigated against the highly inequitable ownership distribution of improved breeds?

Panel A of Table 7 and columns (1)–(4) in Appendix 7 (for additional estimation results) report the estimated coefficients for the censored quantile regressions (using sampling weights) as given by Eq. (6). Because of the highly skewed nature of the improved livestock distribution, we were only able to estimate the censored quantile regressions for the 60th, ..., 90th percentiles, but not the lower percentiles. Also because of collinearity

¹⁶ The negative effect for the CSV dummy in column (2) is unexpected but likely due to collinearity with the piecewise linear control function (equal to zero when CSV=0).

Table 6 Effect of access to savings and credit on adoption of improved small ruminants

	(1) No village and household controls (OLS)	(2) Village and household controls (piecewise linear control function) (OLS)	(3) Village and household controls (OLS)	(4) Household fixed effects (FE)	(5) Household fixed effects (FE)
CSV	0.32*** (0.06)	-1.10** (0.52)	0.29*** (0.05)		
Savings and credit access	0.17*** (0.05)	0.18*** (0.06)	0.17*** (0.05)	0.13** (0.05)	
x (CSV = 1)					0.17*** (0.05)
x (CSV = 0)					0.04 (0.11)
r^2	0.14	0.27	0.25	0.03	0.03
N	350	344	344	350	350

Standard errors are clustered by village and reported in parentheses. Additional estimation results are in Appendix 6. Sample: balanced panel 2012–2017

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

Table 7 Censored quantile regression estimates for impact of CSV interventions and access to credit/savings on number of improved small ruminants (sheep and goats)

	Panel A				
	(1)	(2)	(3)	(4)	
	p60	p70	p80	p90	
CSV	5.24 (5.05)	2.15 (6.63)	-4.00 (7.08)	11.70* (6.81)	
Village controls	Yes	Yes	Yes	Yes	
Household controls	Yes	Yes	Yes	Yes	
Year dummies	Yes	Yes	Yes	Yes	
<i>N</i>	577	577	577	577	
	Panel B				
	(5)	(6)	(7)	(8)	(9)
	p50	p60	p70	p80	p90
Savings and credit access (lagged, dummy)	1.67 (9.62)	2.92 (3.44)	4.32 (3.94)	5.51* (3.20)	8.07*** (2.88)
CSV	2.74 (3.47)	5.54 (7.31)	-7.32 (9.22)	-0.15 (6.49)	11.8* (6.22)
Village controls	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
<i>N</i>	461	461	461	461	461

standard errors are bootstrapped with 100 replications. The censored quantile regressions are estimated following Guirkingier and Boucher 2008 using the CQIV command in Stata (StataCorp 2015), using sampling weights

***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sample: balanced panel 2012–2020

problems, we omitted the dummy for the gender of the household head. The foregoing analysis did not reveal any gender effects (see column (1) in Appendices 1–5). The ownership distribution of improved livestock is affected by location, household characteristics, and initial livestock holdings at the start of CSV intervention (columns (1)–(4) of Appendix 7). Also, the CSV intervention has had an impact on the distribution, but its impact was limited to the upper tail of the distribution (i.e., 90th percentile) (panel A of Table 7). We note, however, that this does not necessarily imply that the CSV intervention did increase the inequality in improved livestock ownership, as the quantile regression estimates are conditional on the included regressors. Therefore, we can only conclude from this that the CSV intervention has affected the conditional improved ownership distributions by shifting the upper tails further outward.

In panel B of Table 7, we re-estimate the percentiles also controlling for (lagged) membership of a savings and credit group (see columns (5)–(9) of Appendix 7 for additional estimation results). We found earlier that the average improved livestock is higher for households that are a member, suggesting that credit constraints limit improved livestock adoption (cf. Table 6). Panel B of Table 7 shows that membership affects especially the upper tail of the distribution. The coefficient for CSV remains unaffected in spite of the positive correlation between the CSV and membership dummies.

Using the censored quantile regression estimates in panel B, we next predict for each observation the 50th to 90th percentiles while imposing the lower limit of zero. We also

Table 8 Impacts of savings and credit groups and CSV intervention on ownership distribution of improved small ruminants in climate-smart villages (Gini coefficients)

		CSV intervention	
		Yes (actual)	No (counterfactual)
		(1)	(2)
	Savings and credit group		
(i)	Yes (actual)	0.87	0.89
(ii)	No (counterfactual)	0.91	0.92

assume that the 10th, 20th, ..., 40th percentiles are equal to zero. For some households, one may expect some of these percentiles to exceed zero, but this will only be the case for a small subset of the sample given the highly skewed distribution of improved livestock. However, because of the limited sample size, we are unable to estimate these below median percentiles.

After pooling all predicted distributions across all households, using the sampling weights to take into account that some types of households have been over- or under-sampled in our survey, we have the predicted distribution for the entire population (i.e., unconditional distribution). We have verified that the predicted distribution matches the actual distribution quite well and far better than when using a more structural approach to the estimation of the distribution (c.q., Poisson's or one of its generalizations—see Appendix 8).

Using the estimated censored quantile regression coefficient of credit, we can predict the counterfactual distribution of the ownership of improved small ruminants when the credit access dummy is set equal to zero, i.e., what the distribution would look like in the absence of a savings and credit group. Column (1) in Table 8 shows that savings and credit access has decreased the Gini coefficient of the ownership of improved breeds in the climate-smart villages by 0.04.

We can also predict the counterfactual distribution when the CSV dummy is set equal to zero, i.e., what the distribution would look like in the absence of the CSV intervention. Given that (virtually) no improved ruminants were present at the start of the CCAFS intervention in both the CSVs and non-CSVs, this counterfactual distribution arguably reflects how the ownership of improved small ruminants would look like if their diffusion was the result of a (spontaneous) spatial rather than planned process (c.q., through spillovers rather than a CCAFS intervention). Row (i) in Table 8 suggests that the CCAFS intervention led to a somewhat lower Gini in improved livestock ownership than in the non-CSVs (0.87 instead of 0.89).

Despite the equalizing effects of the improved access to credit/savings, the improved livestock ownership distributions remain highly skewed and much more so than for indigenous breeds (c.q., Fig. 3), suggesting that the CSV approach was not inclusive enough to introduce the improved livestock technology to all livestock holders equitably.

4 Conclusion and policy implications

4.1 Conclusion

In the current study, we determined the (distributional) impact of CSVs on access to savings and credit and the adoption of improved CSA practices. The main findings

of the study are that the CSV intervention increased the adoption of improved livestock breeds. It also stimulated the membership of savings and loan groups, which in turn stimulated the adoption of improved livestock breeds. These findings point to the importance of community-based savings and loan initiatives to mobilize finance among farmers enabling them to invest in CSA practices. Although the impact on access to savings and credit seems to taper off during the later years of the intervention, the overall positive trend in savings and loan group membership also in the later years suggests that the increase has become self-sustaining. No such sustained increase is found for the adoption of improved livestock despite the estimated positive impact of the CSV interventions, suggesting that additional support would be needed to achieve the envisioned universal adoption of improved breeds. We also found that the introduction of improved breeds was highly inequitable benefitting the larger livestock owners but that the availability of credit has lowered the inequity in the ownership of improved livestock (reducing the Gini by 0.04). Also, the CCAFS-led diffusion of improved livestock in CSVs was somewhat more equitable than the (spontaneous) spill-over diffusion observed in the non-CSVs (reducing the Gini by 0.02).

4.2 Policy implications

Our research outcomes are of importance for policy and practice. As Ogada et al. (2020) conclude, the uptake of improved breeds is a viable pathway out of poverty and improves the resilience of farmers. This requires well-designed, accessible, and affordable breeding programs, while also linkages to output markets are critical for commercialization and sustainability (ibidem). This study complements previous findings since the adoption of improved livestock in the CSVs and membership in savings and credit groups has mitigated the inequality of the initial distribution of improved breeds. Here, our empirical findings complement the literature on the inclusiveness of agricultural innovations (Opola et al. 2021; Hoffecker 2021; Alia et al. 2018) finding that innovations do not always benefit all farms but can be biased toward better-off segments. Policies that strengthen local credit groups would therefore facilitate the uptake of improved breeds more equitably (although ownership distributions of uptake are likely to remain highly skewed for a long time after initial introduction). When replicating the intervention, special attention should be given to further reducing the inequalities, by reviewing the intervention modalities, the possible barriers in the wider production system of improved breeds, and possible other drivers of inequality. The CSA component and the savings group component seem to reinforce each other, at least in reducing the inequalities in the distribution of animals. This calls for further exploring the scalability of this approach, which could take shape in different scenarios. One scenario could be that the package approach is adopted by development actors, such as the Kenyan county governments, or by projects of donors or investors. Another scenario could be that CSA promotion agencies link their activities with CBOs and savings groups and vice versa.

Appendix 1

Table 9 Correlations between village and household characteristics

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Located in Kericho county	1.00													
2. Distance to motorable road	0.03	1.00												
3. Distance to food market	0.28	0.34	1.00											
4. Distance to livestock market	-0.01	0.12	0.06	1.00										
5. Altitude	0.52	-0.08	0.35	0.05	1.00									
6. Household size	-0.16	-0.02	0.09	0.00	-0.02	1.00								
7. Gender of household head	0.09	0.16	0.25	0.15	0.14	0.23	1.00							
8. Age of household head	-0.20	0.08	-0.17	0.10	-0.18	-0.24	-0.16	1.00						
9. Education of household head	-0.14	-0.15	-0.04	0.01	-0.06	0.37	0.27	-0.17	1.00					
10. Ethnicity of household	-0.68	0.07	-0.38	0.10	-0.77	0.12	-0.18	0.23	0.22	1.00				
11. Number of cattle owned before 2012	0.11	-0.27	0.00	-0.01	0.09	0.11	0.03	0.21	0.10	-0.14	1.00			
12. Number of sheep owned before 2012	-0.12	-0.03	-0.02	0.01	-0.11	0.12	0.04	0.19	0.09	0.14	0.25	1.00		
13. Number of goats owned before 2012	0.15	-0.22	-0.07	-0.04	0.20	0.18	0.00	-0.01	-0.01	-0.09	0.40	0.19	1.00	
14. Membership of groups before 2012	-0.25	-0.03	-0.22	0.08	-0.04	0.09	0.10	0.11	0.09	0.15	-0.02	0.02	-0.13	1.00

Table 10 Table 5 panel A, other estimation results (no village and household controls—ordinary least squares)

	(1) Improved live- stock (dummy)	(2) Improved sheep and goats (dummy)	(3) Savings and credit access (dummy)	(4) Use of credit (dummy)	(5) Use of credit for agri- culture (dummy)	(6) Credit for CSA (dummy)	(7) Use of savings (dummy)	(8) Credit- constrained (dummy)
Year 2016	0.11** (0.04)	0.10** (0.05)	0.36*** (0.05)					
Year 2017	0.13*** (0.04)	0.12** (0.04)	0.36*** (0.04)	0.18*** (0.04)	-0.17*** (0.05)			
Year 2019	-0.00 (0.06)	0.01 (0.06)	0.44*** (0.06)	0.20** (0.09)	-0.05 (0.05)			0.01 (0.05)
Year 2020	0.04 (0.07)	0.02 (0.06)	0.44*** (0.06)	0.15* (0.08)	-0.10* (0.06)	-0.05 (0.04)	0.19** (0.08)	0.01 (0.04)
Constant	0.10* (0.06)	0.08 (0.05)	0.21*** (0.05)	0.23*** (0.07)	0.19*** (0.04)	0.09** (0.04)	0.63*** (0.09)	0.09* (0.04)

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2020

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

Table 11 Table 5 panel B, other estimation results (piecewise linear control function—ordinary least squares)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit (dummy)	Use of credit for agriculture (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Credit-constrained (dummy)
Located in Kericho county (dummy, Kericho = 1)	0.08 (0.12)	0.17 (0.16)	0.02 (0.05)	0.07 (0.10)	-0.00 (0.09)	0.09 (0.07)	-0.16 (0.10)	0.12** (0.05)
Distance to motorable road (log, km)	0.04 (0.03)	0.03 (0.03)	0.05*** (0.02)	0.07*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.05** (0.02)	-0.00 (0.01)
Distance to food market (log, km)	0.05** (0.03)	0.07** (0.03)	-0.02 (0.04)	-0.05 (0.03)	-0.03 (0.02)	-0.00 (0.03)	-0.01 (0.05)	-0.01 (0.02)
Distance to livestock market (log, km)	0.19* (0.09)	0.15 (0.10)	-0.16*** (0.05)	-0.03 (0.06)	0.00 (0.04)	0.14*** (0.03)	-0.06 (0.07)	0.04* (0.02)
Altitude (km)	-0.76** (0.33)	-0.57 (0.35)	0.26 (0.26)	0.12 (0.29)	0.27 (0.17)	0.40 (0.36)	-0.50 (0.30)	0.04 (0.12)
Household size	0.03 (0.02)	0.04* (0.02)	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.02)	0.01 (0.02)	0.01 (0.01)
Gender of household head (dummy, male = 1)	0.00 (0.12)	0.02 (0.12)	-0.06 (0.07)	-0.10 (0.10)	-0.07 (0.05)	-0.07** (0.03)	-0.14 (0.08)	0.01 (0.02)
Age of household head (years)	0.00 (0.00)	0.00 (0.00)	-0.00** (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.01** (0.00)	0.00 (0.00)
Education of household head (levels 1–7)	0.06 (0.04)	0.05 (0.04)	0.03** (0.01)	0.06*** (0.01)	0.01 (0.01)	-0.02 (0.02)	0.05** (0.02)	-0.01 (0.01)
Ethnicity of household (dummy, Luo = 1)	-0.16* (0.08)	-0.03 (0.08)	0.03 (0.06)	0.07 (0.08)	-0.00 (0.05)	0.13 (0.09)	-0.11 (0.13)	0.11** (0.05)
Number of cattle owned before 2012	0.00 (0.01)	0.00 (0.01)	0.00 (0.00)	0.01** (0.00)	0.01** (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00** (0.00)
Number of sheep owned before 2012	0.00* (0.00)	0.00** (0.00)	-0.00 (0.00)	-0.01** (0.00)	-0.00* (0.00)	-0.00 (0.00)	0.01** (0.00)	0.00** (0.00)

Table 11 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit (dummy)	Use of credit for agriculture (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Credit-constrained (dummy)
Number of goats owned before 2012	0.01** (0.01)	0.01** (0.01)	-0.01** (0.00)	-0.00 (0.00)	-0.01*** (0.00)	-0.01* (0.00)	0.00 (0.01)	0.00 (0.00)
Membership of groups before 2012 (fraction)	0.10 (0.06)	0.09 (0.07)	0.20*** (0.06)	0.11 (0.09)	-0.03 (0.06)	0.05 (0.08)	-0.02 (0.10)	0.02 (0.04)
Year 2016	0.11** (0.04)	0.11** (0.05)	0.36*** (0.05)					
Year 2017	0.13*** (0.04)	0.12** (0.04)	0.37*** (0.04)	0.18*** (0.04)	-0.17*** (0.05)			-0.00 (.)
Year 2019	-0.00 (0.06)	0.01 (0.06)	0.44*** (0.06)	0.20** (0.09)	-0.06 (0.05)			0.02 (0.05)
Year 2020	0.04 (0.07)	0.02 (0.06)	0.44*** (0.06)	0.16* (0.08)	-0.10* (0.06)	-0.04 (0.05)	0.19** (0.08)	0.02 (0.04)
Constant	0.09 (0.06)	0.08 (0.05)	0.20*** (0.05)	0.23*** (0.07)	0.19*** (0.05)	0.08** (0.04)	0.63*** (0.09)	0.08* (0.04)

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2020

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

Table 12 Table 5 panel C, other estimation results (ordinary least squares)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit (dummy)	Use of credit for agriculture (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Credit-constrained (dummy)
Located in Kericho county (dummy, Kericho = 1)	-0.05 (0.05)	0.02 (0.10)	-0.01 (0.06)	0.05 (0.08)	0.02 (0.06)	0.06 (0.05)	-0.08 (0.09)	0.12*** (0.04)
Distance to motorable road (log, km)	0.03** (0.01)	0.03 (0.02)	0.03** (0.02)	0.04*** (0.02)	0.04*** (0.01)	0.04*** (0.01)	0.02 (0.02)	0.01 (0.01)
Distance to food market (log, km)	-0.01 (0.02)	0.00 (0.03)	-0.07* (0.04)	-0.07*** (0.02)	-0.03*** (0.01)	-0.03** (0.02)	-0.06 (0.04)	0.00 (0.01)
Distance to livestock market (log, km)	0.08** (0.04)	0.05 (0.08)	-0.18*** (0.06)	-0.08* (0.04)	-0.02 (0.04)	0.04 (0.05)	-0.13* (0.08)	0.05*** (0.02)
Altitude (km)	-0.07 (0.25)	0.04 (0.31)	0.58** (0.27)	0.09 (0.38)	0.03 (0.26)	0.18 (0.38)	-0.42* (0.24)	0.06 (0.11)
Household size	0.03*** (0.01)	0.03* (0.02)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Gender of household head (dummy, male = 1)	0.06 (0.06)	0.06 (0.07)	0.02 (0.08)	-0.02 (0.07)	-0.03 (0.05)	-0.02 (0.04)	-0.02 (0.07)	-0.02 (0.03)
Age of household head (years)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01** (0.00)	0.00 (0.00)
Education of household head (levels 1–7)	0.03** (0.01)	0.03 (0.02)	0.01 (0.02)	0.04** (0.02)	0.01 (0.01)	-0.01 (0.02)	0.03* (0.02)	-0.01 (0.01)
Ethnicity of household (dummy, Luo = 1)	-0.15* (0.08)	-0.06 (0.09)	0.01 (0.07)	0.02 (0.11)	-0.06 (0.06)	-0.01 (0.11)	-0.09 (0.12)	0.11** (0.05)
Number of cattle owned before 2012	0.01* (0.00)	0.01** (0.00)	0.01 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	-0.00 (0.00)
Number of sheep owned before 2012	0.01** (0.00)	0.01** (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.01*** (0.00)	0.00* (0.00)

Table 12 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit (dummy)	Use of credit for agriculture (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Credit-constrained (dummy)
Number of goats owned before 2012	0.01*** (0.00)	0.01 (0.01)	-0.01*** (0.00)	-0.00 (0.00)	-0.00** (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Membership of groups before 2012 (fraction)	0.03 (0.05)	0.02 (0.05)	0.17*** (0.06)	0.09 (0.07)	-0.04 (0.05)	0.02 (0.06)	-0.02 (0.07)	0.03 (0.03)
Year 2016	0.11** (0.06)	0.11** (0.05)	0.36*** (0.05)					
Year 2017	0.13** (0.06)	0.12** (0.04)	0.37*** (0.04)	0.18*** (0.04)	-0.17*** (0.05)			-0.00 (.)
Year 2019	-0.00 (0.06)	0.01 (0.06)	0.44*** (0.06)	0.20** (0.09)	-0.06 (0.05)			0.02 (0.05)
Year 2020	0.04 (0.06)	0.02 (0.06)	0.44*** (0.06)	0.16* (0.08)	-0.10* (0.06)	-0.04 (0.05)	0.19** (0.08)	0.02 (0.04)
Constant	-0.10 (0.36)	-0.30 (0.40)	-0.12 (0.34)	0.19 (0.52)	0.20 (0.34)	-0.18 (0.55)	1.70*** (0.32)	-0.24 (0.15)

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2020

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

Appendix 2. Additional results for propensity score matching

The propensity score model

Table 13 Probit estimates for being enlisted in the intervention (marginal effects)

	CSV
Household size	0.08*** (0.03)
Gender of household head (dummy, male = 1)	− 0.15 (0.17)
Age of household head (years)	0.01* (0.00)
Education of household head (levels 1–7)	− 0.01 (0.05)
Ethnicity of household (dummy, Luo = 1)	− 0.59*** (0.17)
Number of cattle owned before 2012	− 0.02 (0.02)
Number of sheep owned before 2012	− 0.00 (0.01)
Number of goats owned before 2012	0.06*** (0.02)
Membership of groups before 2012 (fraction)	0.79*** (0.16)
Constant	− 0.52 (0.37)
<i>N</i>	388
<i>p</i>	< 0.01

Standard errors are reported in parentheses. Sample: cross-Sect. 2017

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

Table 14 Propensity score blocks required for balancing scores across treatment and comparison groups

Propensity score (range)	Number of observations		
	Treated	Comparison	Total
[0.0–0.2)	4	7	11
[0.2–0.4)	34	66	100
[0.4–0.6)	63	68	131
[0.7–0.8)	76	35	111
[0.8–1.0]	39	4	43
Total	216	180	396

Table 15 Balancing tests for covariates (after matching)

	Unmatched Matched	Treated	Control	%bias	% less bias	t	p> t	V(T)/V(C)
Household size	U	6.09	5.54	23.7		2.33	0.02	1.18
	M	6.05	6.11	-2.5	89.3	-0.25	0.80	1.10
Gender of household head (dummy, male = 1)	U	0.71	0.72	-0.5		-0.05	0.96	1.01
	M	0.72	0.71	1.5	-193.4	0.15	0.88	0.98
Age of household head (years)	U	52.1	49.8	15		1.48	0.14	0.84
	M	52.2	52.6	-2.6	82.4	-0.27	0.79	0.96
Education of household head (levels 1-7)	U	3.14	3.21	-4.6		-0.45	0.66	0.94
	M	3.16	3.26	-6.3	-38.8	-0.63	0.53	0.93
Ethnicity of household (dummy, Luo = 1)	U	0.69	0.81	-28.2		-2.78	0.01	-
	M	0.71	0.78	-17.6	37.5	-1.76	0.08	-
Number of cattle owned before 2012	U	3.77	3.05	15.4		1.52	0.13	1.23
	M	3.64	3.74	-2.2	85.5	-0.20	0.84	0.76
Number of sheep owned before 2012	U	2.62	2.73	-1.4		-0.14	0.89	0.31*
	M	2.73	2.85	-1.4	-2.0	-0.17	0.87	0.51*
Number of goats owned before 2012	U	3.69	1.93	36.2		3.53	0.00	2.22*
	M	3.13	3.62	-10.2	71.8	-1.03	0.30	0.59*
Membership of groups before 2012 (fraction)	U	0.36	0.14	51.4		5.02	0.00	-
	M	0.35	0.35	-1.6	96.9	-0.14	0.89	-

*If variance ratio outside [0.76; 1.31] for U and [0.76; 1.32] for M

Balancing

The propensity score method assumes that there is “balancing” in the sense that the propensity score should have a similar distribution (“balance”) in the treated and comparison groups. For this, it is common practice to split the sample by propensity score quintiles first and to check whether the differences in proportions of treatment and comparison groups are not statistically significant. If this is not the case, then one or more quintiles can be split into smaller blocks to see whether balance can be achieved. If not, then the propensity score model needs to be re-specified (Imbens 2004). In our case, balance was found for each of the quintiles (Table 14).

Apart from balancing of propensity scores across the treatment and comparison groups, balancing is also required for covariates across treatment and comparison groups. Although balance in observed covariates does not necessarily indicate balance in unobserved covariates, balance in the former plausibly gives also some support for the claim that unmeasured covariates will not be confounders biasing the treatment effect estimates. While it is possible to test for balancing before applying a matching procedure, any lack of balance is not necessarily problematic as matching will eliminate out most of these differences.

Table 15 presents the results for different types of balancing tests, namely, the standardized percentage bias, *t*-tests for equality of means in the two samples, and the variance ratio, both for the unmatched and matched samples. Imbalance in some covariates is expected, of course (even in RCTs), as the exact balance is a large-sample property. Looking first at the *t*-tests, none of the covariates in the matched samples are significant at 10%. When we consider the two other types of balancing tests, there is also little reason for concern. The reported standardized percentage biases before and after matching (Rosenbaum and Rubin 1985) show large reductions in the (absolute) bias achieved. Although there are no rules about what is acceptable bias, proposed maximum standardized differences range from 10 to 25% (Austin 2009; Stuart et al. 2013). For the matched samples, we find standardized percentage biases of 17.6% or less.

The ratios of variances in the propensity scores between the treated and comparison groups are mostly close to one for the matched samples.¹⁷ This ratio should equal 1 if there is perfect balance. Our ratios fall within the 95% confidence interval for all (continuous) variables (see Austin 2009), except for the number of sheep and goats owned before 2012.

Furthermore, the pseudo R^2 from probit estimation of the propensity score on all the variables is close to zero for the matched sample (0.008), as expected with proper matching. The LR test also rejects the joint significance of all the regressors (*p*-value 0.887).

Overall, we conclude that the matching is successful in balancing the pre-treatment variables. The only exception is a lack of balance in the variances (though not the means) of sheep and goat ownership in the matched samples, likely reflecting the skewness in the livestock distributions which we study in detail further in the paper.

Common support

Propensity score matching requires that there is sufficient common support between treatment and control observations. Figure 4 suggests that the common support requirement is satisfied at all except the very highest values of the propensity score.

¹⁷ These measures are only available for continuous variables.

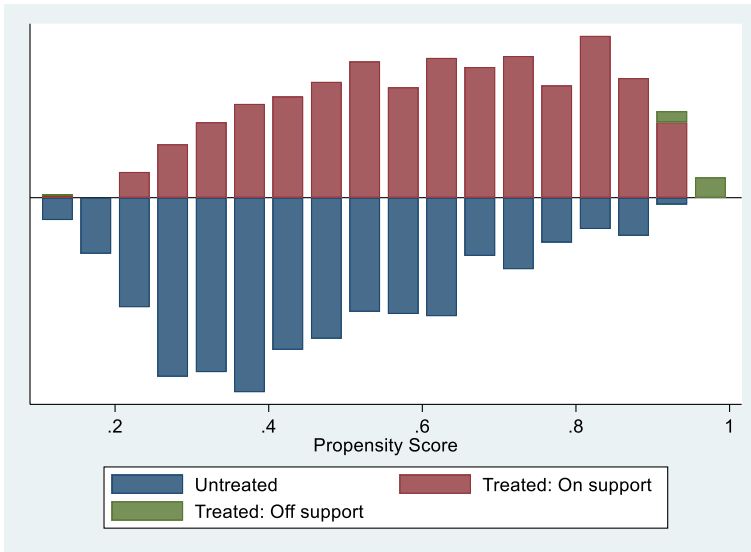


Fig. 4 Common support across treated and untreated observations

Appendix 3

Table 16 Impact of CSV intervention: Heterogeneity across time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit for agriculture (dummy)	Credit-constrained (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Use of credit (dummy)
CSV 2012	0.29*** (0.07)	0.28*** (0.08)	0.31*** (0.08)	0.09 (0.12)	0.08 (0.10)			
CSV 2016	0.32*** (0.08)	0.33*** (0.08)	0.22*** (0.10)					-0.05 (0.06)
CSV 2017	0.35*** (0.07)	0.36*** (0.07)	0.23*** (0.10)	0.13 (0.12)	0.01 (0.04)			-0.05 (0.06)
CSV 2019	0.32*** (0.06)	0.33*** (0.06)	-0.01 (0.10)	0.12 (0.12)	0.08 (0.06)	0.12 (0.08)	0.11 (0.11)	-0.03 (0.07)
CSV 2020	0.19* (0.09)	0.17** (0.08)	-0.01 (0.10)	0.10 (0.14)	0.10* (0.05)	0.06 (0.07)	-0.13* (0.08)	-0.03 (0.06)
Located in Kericho county (dummy, Kericho = 1)	-0.05 (0.09)	0.02 (0.10)	-0.01 (0.06)	0.05 (0.08)	0.02 (0.06)	0.06 (0.05)	-0.08 (0.09)	0.12*** (0.04)
Distance to motorable road (log, km)	0.03* (0.02)	0.03 (0.02)	0.03*** (0.02)	0.04*** (0.02)	0.04*** (0.01)	0.04*** (0.01)	0.02 (0.02)	0.01 (0.01)
Distance to food market (log, km)	-0.01 (0.02)	0.00 (0.03)	-0.07* (0.04)	-0.07*** (0.02)	-0.03** (0.01)	-0.03* (0.02)	-0.06 (0.04)	0.00 (0.01)
Distance to livestock market (log, km)	0.08 (0.07)	0.05 (0.08)	-0.18*** (0.06)	-0.08* (0.04)	-0.02 (0.04)	0.04 (0.05)	-0.13* (0.08)	0.05*** (0.02)
Altitude (km)	-0.07 (0.34)	0.04 (0.31)	0.58*** (0.27)	0.09 (0.38)	0.03 (0.26)	0.18 (0.38)	-0.42* (0.24)	0.06 (0.11)
Household size	0.03* (0.02)	0.03* (0.02)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Gender of household head (dummy, male = 1)	0.06 (0.07)	0.06 (0.07)	0.02 (0.08)	-0.02 (0.07)	-0.03 (0.05)	-0.02 (0.04)	-0.02 (0.07)	-0.02 (0.03)

Table 16 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit for agriculture (dummy)	Credit-constrained (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Use of credit (dummy)
Age of household head (years)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01** (0.00)	0.00 (0.00)
Education of household head (levels 1–7)	0.03* (0.02)	0.03 (0.02)	0.01 (0.02)	0.04** (0.02)	0.01 (0.01)	-0.01 (0.02)	0.03* (0.02)	-0.01 (0.01)
Ethnicity of household (dummy, Luo = 1)	-0.15 (0.10)	-0.06 (0.09)	0.01 (0.07)	0.02 (0.11)	-0.06 (0.06)	-0.01 (0.11)	-0.09 (0.12)	0.11** (0.05)
Number of cattle owned before 2012	0.01* (0.00)	0.01** (0.00)	0.01 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	-0.00 (0.00)
Number of sheep owned before 2012	0.01** (0.00)	0.01** (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.01*** (0.00)	0.00* (0.00)
Number of goats owned before 2012	0.01 (0.01)	0.01 (0.01)	-0.01*** (0.00)	-0.00 (0.00)	-0.00** (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Membership of groups before 2012 (fraction)	0.03 (0.05)	0.02 (0.05)	0.17*** (0.06)	0.09 (0.07)	-0.04 (0.05)	0.02 (0.06)	-0.02 (0.07)	0.03 (0.03)
Year 2016	0.10* (0.06)	0.06 (0.07)	0.42*** (0.10)	0.15** (0.07)	-0.12 (0.08)			-0.00 (.)
Year 2017	0.09* (0.05)	0.06 (0.06)	0.42*** (0.10)					
Year 2019	-0.02 (0.07)	-0.02 (0.07)	0.67*** (0.12)	0.18 (0.13)	-0.06 (0.09)			-0.00 (0.09)
Year 2020	0.12 (0.08)	0.09 (0.08)	0.67*** (0.12)	0.15 (0.15)	-0.12 (0.08)	-0.00 (0.05)	0.36*** (0.12)	-0.00 (0.08)
Constant	-0.10 (0.43)	-0.28 (0.41)	-0.23 (0.33)	0.20 (0.52)	0.19 (0.35)	-0.20 (0.54)	1.61*** (0.32)	-0.23 (0.14)
N	573	573	580	464	464	232	232	464

Table 16 (continued)

	(1) Improved livestock (dummy)	(2) Improved sheep and goats (dummy)	(3) Savings and credit access (dummy)	(4) Use of credit for agriculture (dummy)	(5) Credit- constrained (dummy)	(6) Credit for CSA (dummy)	(7) Use of savings (dummy)	(8) Use of credit (dummy)
r^2	0.24	0.24	0.28	0.12	0.08	0.09	0.22	0.06
p	0.00	0.00	0.28	0.00	0.08	0.00	0.00	0.06

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2020

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

Appendix 4

Table 17 Impact of CSV intervention: Heterogeneity across livestock ownership (quartiles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit for agriculture (dummy)	Credit-constrained (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Use of credit (dummy)
CSV*Q1	0.18 (0.12)	0.15 (0.12)	0.07 (0.10)	0.08 (0.10)	0.05 (0.07)	0.09 (0.06)	-0.15 (0.12)	-0.02 (0.08)
CSV*Q2	0.32* (0.16)	0.31* (0.17)	0.52*** (0.09)	0.30*** (0.11)	0.14** (0.06)	0.20*** (0.07)	0.19* (0.11)	-0.03 (0.06)
CSV*Q3	0.43*** (0.09)	0.46*** (0.07)	-0.06 (0.07)	0.05 (0.10)	0.03 (0.08)	-0.01 (0.13)	-0.03 (0.12)	-0.09 (0.07)
CSV*Q4	0.30* (0.17)	0.29 (0.18)	0.13 (0.12)	-0.00 (0.15)	0.05 (0.08)	0.06 (0.16)	-0.04 (0.11)	-0.02 (0.05)
Located in Kericho county (dummy, Kericho = 1)	-0.04 (0.08)	0.03 (0.10)	0.00 (0.04)	0.06 (0.08)	0.02 (0.06)	0.06 (0.05)	-0.07 (0.09)	0.12*** (0.04)
Distance to motorable road (log, km)	0.03 (0.02)	0.02 (0.02)	0.03** (0.01)	0.04** (0.02)	0.04*** (0.01)	0.04*** (0.01)	0.02 (0.02)	0.01 (0.01)
Distance to food market (log, km)	-0.01 (0.03)	0.00 (0.03)	-0.06* (0.03)	-0.07*** (0.02)	-0.03*** (0.01)	-0.03 (0.02)	-0.06 (0.04)	-0.00 (0.01)
Distance to livestock market (log, km)	0.07 (0.08)	0.04 (0.09)	-0.17*** (0.05)	-0.08* (0.04)	-0.02 (0.04)	0.05 (0.05)	-0.14* (0.07)	0.05** (0.02)
Altitude (km)	-0.06 (0.38)	0.08 (0.36)	0.46* (0.25)	0.06 (0.41)	0.01 (0.26)	0.15 (0.39)	-0.41 (0.25)	0.08 (0.13)
Household size	0.03 (0.02)	0.03 (0.02)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Gender of household head (dummy, male = 1)	0.10 (0.06)	0.09* (0.05)	0.02 (0.07)	-0.01 (0.07)	-0.03 (0.05)	-0.03 (0.03)	0.01 (0.06)	-0.02 (0.03)
Age of household head (years)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01*** (0.00)	-0.00 (0.00)

Table 17 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit for agriculture (dummy)	Credit-constrained (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Use of credit (dummy)
Education of household head (levels 1–7)	0.02 (0.02)	0.02 (0.02)	0.01 (0.02)	0.04** (0.02)	0.01* (0.01)	–0.01 (0.02)	0.03 (0.02)	–0.01 (0.01)
Ethnicity of household (dummy, Luo = 1)	–0.10 (0.11)	–0.02 (0.11)	0.03 (0.06)	0.02 (0.13)	–0.07 (0.06)	–0.03 (0.11)	–0.07 (0.09)	0.11** (0.05)
Number of cattle owned before 2012	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.00)	–0.00 (0.01)	–0.00 (0.01)	0.00 (0.00)
Number of sheep owned before 2012	0.01* (0.00)	0.01* (0.00)	–0.00 (0.00)	–0.00 (0.00)	–0.00* (0.00)	–0.00 (0.00)	0.01** (0.00)	0.00** (0.00)
Number of goats owned before 2012	0.01 (0.01)	0.01 (0.01)	–0.01*** (0.00)	–0.00 (0.00)	–0.00** (0.00)	–0.01* (0.00)	–0.00 (0.00)	0.00 (0.00)
Membership of groups before 2012 (fraction)	0.02 (0.05)	0.02 (0.05)	0.19*** (0.05)	0.09 (0.07)	–0.03 (0.05)	0.02 (0.07)	–0.02 (0.08)	0.03 (0.04)
Livestock Q2	0.06 (0.14)	0.06 (0.14)	–0.22* (0.12)	–0.06 (0.08)	–0.08 (0.08)	–0.07 (0.06)	0.02 (0.16)	0.00 (0.06)
Livestock Q3	0.07 (0.14)	–0.01 (0.11)	0.26** (0.10)	0.09 (0.11)	0.00 (0.06)	0.06 (0.10)	0.13 (0.14)	–0.02 (0.09)
Livestock Q4	–0.01 (0.23)	0.00 (0.24)	0.13 (0.17)	0.17 (0.18)	0.03 (0.10)	0.13 (0.16)	0.17 (0.23)	–0.08 (0.09)
Year 2016	0.11** (0.04)	0.11** (0.05)	0.36*** (0.05)					
Year 2017	0.13*** (0.04)	0.12** (0.04)	0.37*** (0.04)	0.18*** (0.04)	–0.17*** (0.05)			–0.00 (0.00)
Year 2019	–0.00 (0.06)	0.01 (0.06)	0.44*** (0.06)	0.20** (0.09)	–0.06 (0.05)			0.02 (0.05)

Table 17 (continued)

	(1) Improved livestock (dummy)	(2) Improved sheep and goats (dummy)	(3) Savings and credit access (dummy)	(4) Use of credit for agriculture (dummy)	(5) Credit- constrained (dummy)	(6) Credit for CSA (dummy)	(7) Use of savings (dummy)	(8) Use of credit (dummy)
Year 2020	0.04 (0.07)	0.02 (0.06)	0.44*** (0.06)	0.16* (0.08)	-0.10* (0.06)	-0.04 (0.05)	0.19** (0.08)	0.02 (0.04)
Constant	-0.15 (0.51)	-0.37 (0.49)	0.02 (0.33)	0.22 (0.56)	0.22 (0.35)	-0.14 (0.54)	1.69*** (0.31)	-0.23 (0.15)
<i>N</i>	573	573	580	464	464	232	232	464
<i>r</i> ²	0.28	0.27	0.31	0.13	0.08	0.10	0.26	0.07
<i>p</i>	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2020

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

Appendix 5

Table 18 Impact of CSV intervention: Heterogeneity across gender of household head

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Improved livestock (dummy)	Improved sheep and goats (dummy)	Savings and credit access (dummy)	Use of credit for agriculture (dummy)	Credit-constrained (dummy)	Credit for CSA (dummy)	Use of savings (dummy)	Use of credit (dummy)
CSV	0.32*** (0.06)	0.32*** (0.06)	0.12* (0.07)	0.08 (0.08)	0.06 (0.04)	0.10 (0.07)	-0.04 (0.08)	-0.03 (0.04)
CSV*female	-0.14 (0.15)	-0.16 (0.14)	0.15 (0.13)	0.14 (0.15)	0.03 (0.09)	-0.04 (0.10)	0.18 (0.16)	-0.02 (0.07)
Located in Kericho county (dummy, Kericho=1)	-0.05 (0.08)	0.03 (0.10)	-0.02 (0.06)	0.04 (0.08)	0.02 (0.06)	0.06 (0.05)	-0.09 (0.09)	0.12*** (0.04)
Distance to motorable road (log, km)	0.03 (0.02)	0.02 (0.02)	0.03** (0.02)	0.05*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.02 (0.02)	0.00 (0.01)
Distance to food market (log, km)	-0.01 (0.02)	0.00 (0.03)	-0.07* (0.04)	-0.07*** (0.02)	-0.03** (0.01)	-0.03 (0.02)	-0.06 (0.04)	0.00 (0.01)
Distance to livestock market (log, km)	0.08 (0.08)	0.04 (0.08)	-0.17*** (0.05)	-0.08* (0.04)	-0.02 (0.04)	0.04 (0.05)	-0.13* (0.07)	0.05*** (0.02)
Altitude (km)	-0.08 (0.35)	0.02 (0.32)	0.59** (0.26)	0.10 (0.40)	0.03 (0.26)	0.18 (0.38)	-0.41* (0.24)	0.06 (0.11)
Household size	0.03* (0.02)	0.03* (0.02)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
Gender of household head (dummy, male=1)	-0.04 (0.08)	-0.06 (0.07)	0.13 (0.13)	0.08 (0.09)	-0.00 (0.09)	-0.05 (0.10)	0.12 (0.13)	-0.04 (0.06)
Age of household head (years)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01** (0.00)	0.00 (0.00)
Education of household head (levels 1-7)	0.03* (0.02)	0.03 (0.02)	0.01 (0.02)	0.04** (0.02)	0.01 (0.01)	-0.01 (0.02)	0.03* (0.02)	-0.01 (0.01)
Ethnicity of household (dummy, Luo=1)	-0.15 (0.09)	-0.06 (0.09)	0.01 (0.07)	0.01 (0.11)	-0.06 (0.06)	-0.01 (0.11)	-0.09 (0.11)	0.11** (0.05)

Table 18 (continued)

	(1) Improved livestock (dummy)	(2) Improved sheep and goats (dummy)	(3) Savings and credit access (dummy)	(4) Use of credit for agriculture (dummy)	(5) Credit- constrained (dummy)	(6) Credit for CSA (dummy)	(7) Use of savings (dummy)	(8) Use of credit (dummy)
Number of cattle owned before 2012	0.01 (0.00)	0.01* (0.00)	0.01 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	-0.00 (0.00)
Number of sheep owned before 2012	0.01** (0.00)	0.01** (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.01*** (0.00)	0.00* (0.00)
Number of goats owned before 2012	0.01 (0.01)	0.01 (0.01)	-0.01*** (0.00)	-0.00 (0.00)	-0.00** (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Membership of groups before 2012 (fraction)	0.02 (0.05)	0.02 (0.05)	0.18*** (0.06)	0.10 (0.08)	-0.04 (0.05)	0.02 (0.06)	-0.01 (0.08)	0.03 (0.03)
Year 2016	0.11** (0.04)	0.11** (0.05)	0.36*** (0.05)					
Year 2017	0.13*** (0.04)	0.12** (0.04)	0.37*** (0.04)	0.18*** (0.04)	-0.17*** (0.05)			-0.00 (0.00)
Year 2019	-0.00 (0.06)	0.01 (0.06)	0.44*** (0.06)	0.20** (0.09)	-0.06 (0.05)			0.02 (0.05)
Year 2020	0.04 (0.07)	0.02 (0.06)	0.44*** (0.06)	0.16* (0.08)	-0.10* (0.06)	-0.04 (0.05)	0.19** (0.08)	0.02 (0.04)
Constant	0.01 (0.47)	-0.16 (0.45)	-0.23 (0.36)	0.09 (0.60)	0.18 (0.36)	-0.15 (0.54)	1.57*** (0.30)	-0.22 (0.17)
N	573	573	580	464	464	232	232	464
r ²	0.24	0.24	0.27	0.12	0.07	0.09	0.20	0.06
p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2020

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

Appendix 6

Table 19 Other estimation results for Table 6

	(1) village and household controls (piecewise linear control function) (OLS)	(2) village and household controls (OLS)
Located in Kericho county (dummy, Kericho = 1)	0.20 (0.21)	0.04 (0.13)
Distance to motorable road (log, km)	0.03 (0.04)	0.02 (0.02)
Distance to food market (log, km)	0.05** (0.03)	0.00 (0.02)
Distance to livestock market (log, km)	0.15 (0.13)	0.07 (0.09)
Altitude (km)	0.35 (0.48)	0.64 (0.41)
Household size	0.03 (0.02)	0.02 (0.02)
Gender of household head (dummy, male = 1)	0.01 (0.15)	0.09 (0.10)
Age of household head (years)	0.00 (0.00)	− 0.00 (0.00)
Education of household head (levels 1–7)	0.03 (0.04)	0.02 (0.02)
Ethnicity of household (dummy, Luo = 1)	0.09 (0.11)	0.06 (0.13)
Number of cattle owned before 2012	0.00 (0.00)	0.01 (0.00)
Number of sheep owned before 2012	0.01** (0.00)	0.01** (0.00)
Number of goats owned before 2012	0.01 (0.01)	0.01 (0.01)
Membership of groups before 2012 (fraction)	0.05 (0.09)	− 0.02 (0.05)
Constant	0.07 (0.05)	− 1.15** (0.55)

Standard errors are clustered by village and reported in parentheses. Sample: balanced panel 2012–2017

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

Appendix 7

Table 20 Other estimation results Table 7

	Additional results for panel A in Table 7				Additional results for panel B in Table 7				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	p60	p70	p80	p90	p50	p60	p70	p80	p90
Located in Kericho county (dummy, Kericho = 1)	5.14 (3.94)	3.19 (3.48)	4.12 (3.23)	0.39 (2.50)	3.26 (4.48)	4.94 (4.06)	4.88 (3.76)	5.16* (2.95)	0.49 (2.96)
Distance to motorable road (log, km)	1.04 (1.40)	0.07 (0.86)	0.63 (0.67)	1.28** (0.64)	0.72 (1.36)	1.29 (0.99)	1.70 (1.13)	0.44 (0.77)	0.72 (0.62)
Distance to food market (log, km)	1.45 (1.46)	0.94 (1.42)	0.83 (1.19)	-0.64 (1.09)	1.01 (1.55)	1.58 (1.79)	1.81 (1.51)	0.42 (1.47)	0.96 (1.29)
Distance to livestock market (log, km)	13.6** (6.01)	4.15 (4.54)	5.91 (3.63)	6.12** (3.01)	11.1 (6.79)	14.7** (6.34)	10.1* (5.44)	6.94* (3.99)	9.15*** (3.05)
Altitude (km)	-51.4** (24.6)	-8.33 (20.4)	-21.1 (15.1)	-1.19 (13.1)	-42.0 (31.2)	-59.2* (30.4)	-36.1 (22.6)	-21.1 (16.1)	-10.5 (13.5)
Household size	2.76** (1.27)	0.15 (0.84)	0.86 (0.75)	1.18** (0.58)	2.19 (1.83)	3.16** (1.45)	1.57 (1.01)	1.41** (0.70)	1.49*** (0.57)
Age of household head (years)	-0.25* (0.13)	-0.06 (0.10)	-0.11 (0.10)	-0.08 (0.08)	-0.09 (0.11)	-0.17 (0.13)	-0.12 (0.11)	-0.07 (0.10)	-0.03 (0.08)
Education of household head (levels 1–7)	3.48* (1.78)	1.11* (1.51)	2.36** (1.17)	0.81 (0.70)	3.55* (1.99)	4.49*** (1.70)	3.31** (1.53)	1.12 (0.99)	0.83 (0.71)
Ethnicity of household (dummy, Luo = 1)	-20.0*** (9.65)	-1.50 (7.67)	-10.3* (5.68)	-8.39* (4.43)	-17.6* (9.96)	-22.0*** (9.46)	-11.1* (6.21)	-7.11 (4.81)	-10.1** (4.29)
Number of cattle owned before 2012	0.18 (0.33)	0.24 (0.31)	0.11 (0.30)	0.48 (0.41)	0.16 (0.40)	0.23 (0.34)	0.15 (0.30)	0.23 (0.32)	0.82* (0.42)
Number of sheep owned before 2012	0.96** (0.40)	0.43 (0.33)	0.90*** (0.29)	1.09*** (0.22)	0.70* (0.37)	0.95*** (0.32)	0.89*** (0.36)	0.90*** (0.27)	0.86*** (0.21)
Number of goats owned before 2012	0.75** (0.31)	0.22 (0.28)	0.40* (0.22)	0.40* (0.22)	0.58* (0.32)	0.61* (0.36)	0.54** (0.24)	0.29 (0.20)	0.17 (0.23)

Table 20 (continued)

	Additional results for panel A in Table 7				Additional results for panel B in Table 7				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	p60	p70	p80	p90	p50	p60	p70	p80	p90
Membership of groups before 2012 (fraction)	3.03 (2.18)	-0.23 (2.01)	2.19 (2.64)	1.01 (1.96)	2.59 (2.44)	2.42 (2.18)	3.42 (2.50)	0.07 (2.45)	-1.78 (2.05)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.0 (20.3)	-4.16 (18.8)	12.2 (19.6)	-22.0 (22.5)	5.11 (23.4)	9.76 (23.4)	18.4 (25.6)	5.05 (21.8)	-22.6 (21.7)

standard errors are bootstrapped with 100 replications. The censored quantile regressions are estimated following Chernozhukov et al. 2015 using the CQIV command in Stata, using sampling weights

***, **, and * indicate significance at the 1%, 5%, and 10% levels. Sample: balanced panel 2012–2020

Appendix 8

Table 21 Gini coefficients for actual versus predicted distribution

	All villages	Only climate-smart villages
Actual distribution	0.92	0.87
Predicted distribution		
Censored quantile regression	0.90	0.87
Poisson	0.72	0.67
Negative binomial	0.81	0.74
Generalized negative binomial	0.81	0.74

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Data availability The dataset generated and analyzed during the current study are not publicly available due to GDPR issues but are anonymized and available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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