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ORIGINAL PAPER

Impacts of climate-smart crop varieties and livestock breeds on the food security of smallholder farmers in Kenya

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Abstract

This paper analyses the impact of climate-smart agriculture (CSA) technologies on household dietary diversity and food insufficiency as indicators of food and nutrition security in Kenya. Using a combination of Propensity Score Matching and endogenous treatment effect approaches, we found that adoption of stress-tolerant varieties of several crops (such as bean, pigeon pea, cowpea, maize and sorghum) improved household dietary diversity score by 40% and reduced food insufficiency by 75%. Adoption of improved and resilient livestock breeds (including Red Maasai sheep and Galla goats) improved household dietary diversity by 38% while reducing household food insufficiency by 90%. We also found that stress-tolerant crop varieties were more effective in improving food security outcomes among households with large landholdings and with more educated and younger to middle-age heads. Effects of resilient livestock breeds on household food security were much stronger for households with large landholdings and with young and/or much older heads that have low levels of education. Given the large, demonstrated benefits from the use of the CSA technologies, policies and programs aimed at their promotion should apply appropriate targeting to ensure wider uptake of the technologies and maximum returns on investment.

Keywords Climate-smart agriculture · Household food security · Propensity score matching · Endogenous treatment effect · Smallholder farmers · Kenya

JEL Classification Q16 · Q54 · O33 · D12

1 Introduction

Climate change, manifested in rising temperatures, erratic rainfall patterns and increased frequency and severity of extreme weather conditions is emerging as a major threat to agriculture and economic development in many developing countries. Climate change impacts agriculture through various pathways due to the combined effects of temperature and precipitation. Globally, agriculture is the largest user of water. IPCC assessments show that climate-induced changes in the global hydrological cycle are already impacting agriculture through floods, droughts, and increased rainfall variability, which have affected the yields of major staple crops, thus increasing the number of people experiencing food insecurity (IPCC, 2019, 2021, 2022; Seneviratne et al., 2021; WMO, 2020). These changes are projected to continue in a warmer world, but the overall changes expected differ across models, regions, and seasons. In addition to climate change, land-use change and land-use intensification

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are contributing to desertification and land degradation (IPCC, 2019).

Vulnerability to climate impacts on food security and nutrition vary by region. Regions such as Sub-Saharan Africa (SSA) that experience climate impact drivers such as extreme heat, severe drought or floods, and have a large proportion of the population dependent on rainfed agriculture, have experienced rising food insecurity (FAO et al., 2018; Mbow et al., 2019). In SSA, vulnerability to climate change impacts on food insecurity and malnutrition is compounded by other underlying factors including poverty, multiple forms of inequality (e.g., gender, income), low access to water and sanitation, macroeconomic shocks, and conflict.

The climate drivers relevant to food security (food production and availability) include shifts in climate envelopes that cause shifts in crop varieties planted; seasonal changes (e.g., due to warming trends extending growing seasons); extreme events such as high temperatures affecting critical growth periods for crops, flooding and droughts; and changes in atmospheric conditions such as carbon dioxide concentrations. Moreover, the water resources for crop and livestock production are likely to be affected through changing rates of precipitation and evaporation and ground water levels, among others. The resulting shortened and variable growing seasons, land degradation, shrinking arable land and declining crop yields and livestock productivity (Connolly-Boutin & Smit, 2016), make smallholder agriculture more difficult and risk-prone. The implications for agricultural production and food security are particularly severe for rainfed agricultural production systems, especially in SSA, where about 70% of households depend on rain-fed agriculture (Nelson et al., 2014). While most studies focus climate change impacts on food availability through impacts on food production, climate change is projected to negatively affect all four pillars of food security: availability, access, utilization and stability through both direct and indirect pathways (FAO et al., 2018; IPCC, 2022). Food availability is affected by negative impacts of climate change and variability on productivity of crops and livestock resulting from increases in temperature and changing rainfall patterns, extreme climate events (droughts and floods) (Nicholson, 2017) and increased incidence of pests and diseases (e.g., desert locusts). Increasing incidence and intensity of adverse climate events affect food access and its stability through reduced availability, increased local price volatility, reduced livelihoods for food producers (affecting purchasing power) and disruption to food transport (Gitau et al., 2018). Food utilization is directly affected by climate change through food safety, dietary diversity, and food quality due to increases in mycotoxins in food and feed with rising temperatures and increased frequencies of extreme events, and indirectly through effects on health.

In East Africa, droughts have become more frequent and severe, with prolonged droughts occurring predominantly in the arid and semi-arid areas (Haile et al., 2020). Farmers are responding to and coping with these climate-related risks through short- and long-term strategies while adapting to climate change through a combination of on-farm and off-farm strategies. Some of these strategies include on-farm water and soil conservation; changing cropping patterns; adopting improved crop varieties and shifting to new crops; improved agronomic practices; adopting improved and stress tolerant livestock breeds; migration; and income diversification (Babatunde & Qaim, 2010; Burney & Naylor, 2012; Karamba et al., 2011). Other strategies include use of climate information and indigenous (local) knowledge to inform farmer decisions of what to grow and when to grow it and planning of livestock movements (Birachi et al., 2020; Radeny et al., 2019). To address risks of market-related volatility coupled with climate change, farmers also adopt economic and financial instruments such as index-based crop and livestock insurance. While most of these strategies are beneficial across multiple indicators (water saving, increased incomes, and others), some strategies are sub-optimal, often leading to marginal rather than transformative adaptation to climate change (Gbegbelegbe et al., 2018; Kristjanson et al., 2012; Nyasimi et al., 2017). Building resilience of smallholder agricultural systems to climate change therefore requires investment in appropriate technologies, institutions and policies that provide impetus for transformative change (Thornton et al., 2019). The interventions must, however, be context-specific and targeted.

One such intervention that is increasingly used as an approach for integrated development is climate-smart agriculture (CSA), which addresses food security and climate change challenges in a joint and synergistic manner (Aggarwal et al., 2018; FAO, 2013; Lipper et al., 2014). CSA refers to agriculture that sustainably increases agricultural productivity, builds resilience and adaptive capacity of farming communities, reduces emission of greenhouse gases where possible, and enhances achievement of national food security and development goals (FAO, 2013). Many existing agricultural practices and technologies already provide proven benefits to farmers' food security, resilience, and productivity. Agroforestry, for example, is widely regarded as a strategy for addressing climate change adaptation and mitigation, improving low agricultural productivity, and contributing to household food security (Coulibaly et al., 2017; Mbow et al., 2014; Smith et al., 2020). Other agricultural practices such as soil and water management that enhance soil organic matter also sequester carbon, while offering climate resilience and adaption benefits of improved soil quality, water retention, and reduced erosion. To generate evidence on the efficacy of climate-smart options, the CGIAR Research Program on Climate Change, Agriculture and Food

Security (CCAFS) has been implementing the Climate-Smart Villages (CSVs) Research for Development (R4D) approach in select East African villages. Through participatory research, the program tests climate-smart technological and institutional options for dealing with climate change in agriculture to draw lessons for scaling -out and -up appropriate CSA practices (Aggarwal et al., 2018). CSVs are clusters of villages in climate change hotspots within which researchers, local organizations and farmers collaborate to test the suitability of a portfolio of CSA technologies and/or innovations.

The portfolio of CSA technologies tested is based on farming systems, agro-ecosystems, livelihoods, and the environmental and climate-risk profile of the CSVs. Among the CSA technologies that CCAFS and partners have been testing and promoting in East Africa since 2012 are multiple stress-tolerant varieties of important food crops (DTC in some figs) and resilient small ruminant livestock breeds (IL in some figs). Crop varieties tested include improved varieties of legumes (bean, pigeon pea and cowpea) and cereals (maize and sorghum) and these were accompanied with improved agronomic practices such as the efficient use of fertilizers, optimized planting time and spacing, planting in rows, and integrated pest management (IPM). The improved small ruminant livestock promoted included breeds of Red Maasai sheep and Galla goats that mature faster compared to indigenous breeds, are resistant to internal parasites, have better feed efficiency and are tolerant to trypanosomes, drought, and heat stress. Introduction of these livestock breeds was accompanied with improved livestock management practices (see Nyasimi et al., 2017; Radeny et al., 2019; Recha et al., 2016). This study focussed exclusively on adoption of the multiple stress-tolerant crop varieties and resilient livestock breeds.

Preliminary evidence from the CSVs of East Africa showed noticeable changes, with farmers expanding their crop choices and varieties for higher productivity (Kinyangi et al., 2015; Recha et al., 2015, 2016). Innovations such as cereal-legume intercrops are also increasingly being applied. What is not fully understood is the extent to which the changes have translated into improved household food and nutrition security, a critical objective of CSA. Adoption of CSA technologies is expected to directly deliver productivity gains that increase the availability of food for consumption while reducing costs of production (Aggarwal et al., 2018; Ali & Erenstein, 2017; Becerril & Abdulai, 2010; Kabubo-Mariara & Mulwa, 2019; Langyintuo & Mungoma, 2008; Mendola, 2007; Moyo et al., 2007). Direct impacts could also result from increased income associated with sale of surplus production. Indirectly, increased supply of food staples can lower and stabilize market prices, making food staples accessible and affordable. Additionally, increased farm productivity could heighten demand for farm labour, thus improving incomes of labour-supplying households.

Previous studies show mixed results from adoption of improved agricultural technologies and innovations. While some technologies have been found to improve household expenditure on consumption and reduced poverty (Amare et al., 2012; Asfaw et al., 2012; Kassie et al., 2011; Kiiza & Pederson, 2012; Simtowe et al., 2019), other studies show that improved agricultural technologies may hurt the welfare of the poor households or only have modest impacts (Bourdillon et al., 2007; Gabre-Madhin & Haggblade, 2004; Hossain et al., 2003). Impacts therefore depend on intensity and complementarity in adoption, local context, farm heterogeneity and efficiency of use, among other factors (Amare et al., 2012; Asfaw et al., 2012).

Considering these mixed results, this study used household survey data from the Nyando Basin of Western Kenya to evaluate the impacts of CSA on household food and nutrition security. The paper extends the literature on CSA and food security by analysing heterogeneous effects of adopting multiple stress-tolerant crops and resilient small ruminant breeds, making a comparison of food security outcomes from adopting the two sets of technology. To the best of our knowledge, previous analyses have not considered impacts in such a diversified manner that integrates both heterogeneity and crop-livestock comparisons. We used two complementary measures of food security: *Household dietary diversity score (HDDS),* which indicates the variety of food consumed over a specific period and can therefore be indicative of nutrition security (Roba et al., 2019) and *household food insufficiency*—the number of months in a year in which households struggle to find sufficient food for their families (Kristjanson et al., 2012). Evaluating adoption impacts of the two technologies is complicated by the potential endogenous program placement. The analysis therefore combined propensity score matching with treatment effect models to control for endogeneity and thus provide efficient estimates of impacts.

The rest of this article is organized as follows. In the next section, we present materials and methods used before a presentation and discussion of the results. Finally, we draw conclusions and discuss policy implications of the findings.

2 Materials and methods

2.1 Study area and data collection

Data for this study were collected from Nyando Basin of Western Kenya in 2017. The farming system in the area is predominantly subsistence rain-fed mixed crop-livestock. The basin has a humid to sub-humid climate with bimodal rainfall patterns, averaging between 900 mm and 1,200 mm rainfall annually. The long rains occur in March–May, while the short rains are experienced in September–November (Bargues Tobella, 2010; Verchot et al., 2007). Temperature ranges from 15 to 32 °C. The area has experienced increased frequency and intensity of extreme weather events such as droughts and floods in recent years (Rarieya & Fortun, 2010). Historical data indicate that onset of rain has shifted by about one month while the length of the main growing season has shortened. Land degradation, soil erosion, and declining soil fertility, organic matter and carbon stocks are major environmental challenges for Nyando (Rarieya & Fortun, 2010). Consequently, farm productivity is low, resulting in rising poverty and food and nutrition insecurity. These changes notwithstanding, agriculture remains the mainstay of livelihood, providing food and household income.

This study used a cross-section survey to evaluate impacts of adopting multiple stress-tolerant crops and resilient livestock breeds on household food and nutrition security. While CCAFS has been collecting monitoring data from households within the CSVs in Nyando since 2012, non-participating households were not monitored, and thus the monitoring data could not be used for impact evaluation. A cross-sectional survey of households was therefore conducted by an independent impact evaluator using Computer Assisted Personal Interviews (CAPI), and data collected from 433 randomly selected households - 216 from the CSVs and 217 from the non-CSVs. To minimize placement bias, non-CSVs were identified from areas with similarities to the CSVs in terms of observable biophysical (temperature, precipitation, soil type and landscape) and socio-economic characteristics (most prevalent farming system, main agricultural crops, livestock ownership and husbandry practices and market behaviours). These villages were selected from reasonably distant areas from the CSVs to minimize potential "*contamination*".

Data collected included household demographics, adoption of crop varieties and livestock breeds (including changes in these over time), land use management, off-farm income sources, and access to production information. Additional data included food access and consumption. Specifically, households were asked whether anyone in the household consumed any food from the 12 food groups: cereals; root and tubers; vegetables; fruits; meat, poultry offal; eggs; fish and sea food; pulses/legumes/nuts; milk and milk products; oil/fats; sugar/honey; miscellaneous. This information was then used to calculate HDDS following Swindale and Bilinsky (2006). HDDS is preferred as it is highly correlated with calorific, protein and nutrient adequacy, household income and child nutritional status (see Swindale & Bilinsky, 2006; Webb et al., 2006). Households were also asked to indicate in which months over the reference period they had trouble finding sufficient food. This information was used to construct household food insufficiency.

2.2 Methodology

Estimating impacts of adopting multiple stress-tolerant crops (DTC) and resilient livestock breeds (IL) on food security outcomes is complicated by potential endogeneity in intervention placement. Accurate measurement of impact requires controlling both observable and unobservable factors through random assignment of individuals into adoption. In the absence of random assignment, the observed and unobserved characteristics of individual households may influence adoption as well as the food security outcomes. Since interventions in the Nyando basin did not randomly assign household into adoption of the two interventions, we controlled for potential selection bias in our impact assessment using a combination of propensity score matching (PSM) and treatment effect models based on extended regression models. For this study, adoption was defined as a dummy, indicating households that have used multiple stress-tolerant crops and resilient small ruminant breeds over the reference period and were still using the technologies at the time of the survey. This is irrespective of the proportion of land under the technology or proportion of the herd that is of resilient nature.

2.2.1 Propensity scores matching estimation

The PSM approach matches each CSA technology adopter with a "similar" non-adopter and estimates treatment effect as the average difference in outcome between the matched adopters and non-adopters. The PSM estimator investigates how the food security status of a household would have changed had the CSA adopting households chosen not to adopt respective CSA technologies. Following Imbens and Wooldridge (2009) the average treatment effect on the treated (ATT) is defined as:

$$ATT = E[R(1) - R(0)|I = 1] \tag{1}$$

where R_1 and R_0 are outcomes for households that have applied CSA practices and the comparison group of households, respectively; $I = 1$ indicates that households practice CSA and $I = 0$ refer to comparison group of households that do not practice CSA. However, we can only observe $E[R(1)|I = 1]$ given our cross-sectional data, since we cannot observe food security outcome for adopters had they not adopted CSA technologies. If we simply compare food security outcomes for households with and without adoption, we will introduce a bias in estimation due to self-selection bias, which is estimated as:

$$E[R(1) - R(0)|I = 1] = ATT + E[R(0)|I = 1 - R(0)|I = 0] \tag{2}$$

To address the potential bias, PSM restricts comparison of outcomes to households that are similar in terms of observable characteristics, thereby reducing the bias that would otherwise occur if the two groups were systematically different (Dehejia & Wahba, 2002). PSM therefore creates comparable counterfactual households for the adopters and matches households based on observable characteristics, thus reducing bias due to observables. Additionally, PSM assumes that once households have been matched on observables, there is no systematic difference in unobserved characteristics between adopters and non-adopters (Heckman & Navarro-Lozano, 2004). If this assumption of conditional independence holds, and the overlap is achieved, ATT can be computed as follows:

$$ATT = E\left[R(1)|I = 1, p(x)\right] - E\left[R(0)|I = 0, p(x)\right] \tag{3}$$

2.2.2 Endogenous treatment effect estimation

While the PSM procedure allows comparison of outcomes between comparable groups of households leading to good estimates of the treatment effects, the procedure does not address selection bias due to unobserved factors, which is occasioned by non-random assignment of households into adoption of CSA technologies.

One commonly used approach to model the unobserved heterogeneity is through panel data techniques (Barros et al., 2020). However, panel data analysis does not eliminate other sources of endogeneity such as omitted variables, measurement errors and simultaneity. Moreover, this study did not have the benefit of panel data since the monitoring data was limited to treated households in the CSVs. The study therefore addressed the selection bias due to unobservable through endogenous treatment effect regression models. Following Maddala (1986), impact of adoption of CSA technologies on household food and nutrition security can be expressed as:

$$y = X\beta + \gamma I + \omega \tag{4}$$

where y is the household food and nutrition security indicator; X is a vector of farm, household and contextual characteristics that could influence household food security status and; I is a dummy indicating the household CSA adoption status and, ω is the error term. We hypothesize that the CSA technologies are positively correlated with household food and nutrition security indicators. Other factors remaining constant, the coefficient (γ) therefore captures partial effects of household adoption of CSA technologies. However, there may be unobserved factors that jointly influence adoption and outcome variables. These include individual ingenuity, innate ability and attitudes that cause people to seek for solutions. This implies that the indicator of adoption in Eq. (4) will be correlated with the error term (ω), i.e., [$\rho_{Iu_1} \neq 0$], leading to a biased estimation of γ. The adoption variable therefore needs to enter Eq. (4) not as observed but as an estimated variable: $I = Z\alpha - \eta$; where α is a vector of parameters, Z is a set of variables influencing adoption of CSA technologies and η is an error term with zero mean and variance, σ^2. However, since the unobserved variables also influence adoption of CSA technologies, $I = Z\alpha - \eta$ can be expressed as:

$$I = Z\alpha + u_2 \tag{5}$$

where $u_2 = \eta + \varepsilon$ is the "augmented" error term with ε accounting for unobserved factors that influence adoption of CSA technologies. For each household, adoption of CSA technologies is expected yield food security outcomes, which we denote as Y_i. This outcome is therefore a function of observed factors such as household characteristics, institutional, locational and cultural factors (X_i), CSA technology adoption (I_i), *unobservable factors*(ε_i) and the error term (ω_i) which is independently and identically distributed as normal, i.e., $Y_i = f(X_i, I_i(Z_i, \eta_i), \varepsilon_i, \omega_i)$. Following this expression, Eq. (4) can therefore be represented as:

$$y = X\beta + \gamma(z\alpha + u_2) + u_1 \tag{6}$$

where $u_1 = \omega + \varepsilon$, is an augmented error term with ε accounting for unobserved factors that influence both food security/nutrition outcomes and adoption of CSA technologies. Since the unobserved factors influence both the outcome variable ($u_1 = \omega + \varepsilon$) and adoption ($u_2 = \eta + \varepsilon$), $\rho_{u_1u_2} \neq 0$. Equation (6) can be estimated via endogenous treatment effect models that jointly estimate auxiliary probit model for adoption of CSA technologies and treatment effect, allowing for efficient estimates of γ. One way to estimate this model is via the *standard endogenous switching regression (ESR)* models. However, we suspect that household income, a potential determinant of food security outcomes, could also be endogenous. So, income enters Eq. 6 as an estimated variable based on extended treatment effect models that allows for simultaneous modelling of 2 or more endogenous variables. Extended treatment effect (ETE) models allow for other *endogenous covariates alongside endogenous treatment* as elaborated in STATA manual under "extended regression models" (StataCorp, 2017). Moreover, the model estimates the correlation coefficient ($\rho_{u_1u_2}$), which provides a standard test of endogeneity. Postestimation procedures also yield average treatment effects on the treated (ATT).

Estimation of Eq. (6) requires instrumental variables, which enables identification of the causal effect of adoption. These should be variables that directly affect adoption of climate smart technologies, but do not have a direct effect on the two food security outcomes. We therefore use a selection of variables representing *peer influence* and sourcing of climate/weather related information. For peer influence, we estimate the number of households in the village, *other than the respondent household*, who have introduced new crop varieties and livestock breeds in the past five years. We expect that common practices among other members of the village are likely to influence behaviour of respondent households leading to adoption of improved crop varieties and livestock breeds. Additionally, we also estimate the frequency in sourcing of inputs from agrovet shops by households in the village other than the respondent household. Agrovet shops in Kenya have emerged as an alternative advisory service provider in the wake of dwindling publicly provided extension services. More interaction with agrovet shops could therefore enhance adoption of new crop varieties or may sustain use of non-drought tolerant varieties if the new varieties have not yet penetrated local seed systems. Finally, we also include sources of information on climate and/or weather-related information as a possible instrument in the adoption equation.

Following Di Falco and Veronesi (2013) and Di Falco et al. (2011), we performed a falsification test to establish the admissibility of the suggested instruments. Results of this test are shown in Table 9 in the Appendix where we confirm validity of these instruments: that they are jointly statistically significant determinants of adoption of multiple stress-tolerant crop varieties ($\chi^2 = 26.5$; $p = 0.000$) and resilient livestock breeds ($\chi^2 = 19.9$; $p = 0.001$). However, the instruments are jointly statistically insignificant in the outcome models.

3 Results and discussion

In this section we present our findings beginning with descriptive statistics. Thereafter, we present determinants of adoption before examining the treatment effect estimation. We also analyse heterogeneity in impacts.

3.1 Descriptive statistics

Our descriptive analysis begins with a focus on households in the CSVs in Nyando, where various CSA interventions and innovations for enhancing adaptive capacity have been implemented since 2012. From intervention efforts, households in CSVs have increasingly adopted CSA technologies. Adoption of stress-tolerant varieties of crops (DTC) and improved small ruminants (IL) has been on an upward trend since 2011 (Fig. 1).

Households adopting multiple stress-tolerant crop varieties and resilient small ruminant livestock breeds also experience improved food security (Fig. 2). These households reported a decline in the number of months of food insufficiency. While in 2011 approximately 65% of households in Nyando CSVs were experiencing more than five months of food insufficiency throughout the year (Mango et al., 2011), this proportion had fallen to less than 2% by 2016. The number of households experiencing more than five hunger months annually declined consistently between 2012 and 2016. About 10% of the households reported no food insufficiency throughout the year in 2016, up from about 6% who did so in 2012. These improvements are correlated with the

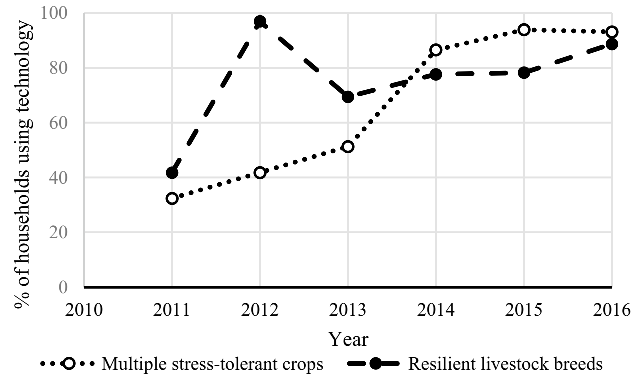

Fig. 1 Trends in uptake of multiple stress-tolerant crops (DTC) and resilient small ruminant livestock – IL among households in the CSV of Nyando basin, Kenya

adoption of multiple stress-tolerant crop varieties and resilient small ruminant breeds as illustrated in Fig. 1.

Using the entire dataset that comprises adopters and non-adopters in the CSVs and the control villages, we see from Table 1 that adopters and non-adopters of multiple stress-tolerant crop varieties differed significantly in farming experience, age, household social capital and access to weather information. Adopters had more farming experience, larger households and better access to weather forecast information. Adopters were also older than the non-adopters and had smaller landholdings as compared to non-adopters. About 76% of the households had adopted improved stress tolerant crop varieties, mainly of maize, and adoption levels were higher in the CSVs than the non-CSVs. Adoption of improved livestock breeds was also higher in the CSVs. The adopters showed superiority in terms of household welfare outcome indicators such as household dietary diversity, household income and domestic asset index.

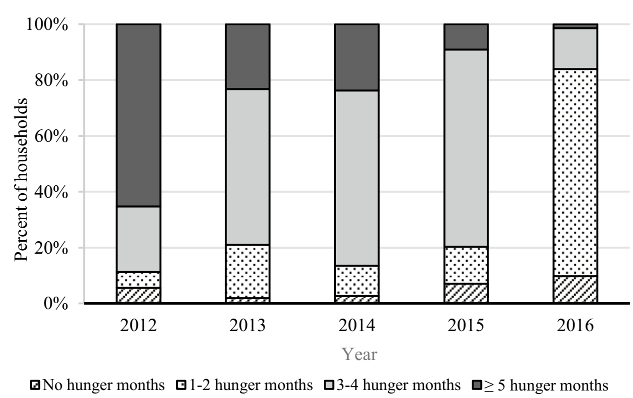

Fig. 2 Trends in household food security in climate smart villages in Nyando, Kenya

Table 1 General differences between adopters and non-adopters of Climate Smart Agriculture (CSA) technologies

	Multiple stress-tolerant crops				**Improved small ruminant livestock**			
	Adopters (n = 208)		Non-adopters (n = 225)		Adopters (n = 131)		Non-adopters (n = 302)	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Resident in CSVs *(%)*	66.3***	3.3	34.7	3.2	79.8***	4.2	41.6	2.7
Household dietary diversity *(count)*	6.452***	0.095	6.093	0.097	6.553**	0.134	6.186	0.079
Domestic asset index	39.284***	3.366	26.039	3.325	39.495*	4.831	30.434	2.730
Annual household income (000)	277.8***	47.7	118.03	129.6	201.23	35.28	193.0	29.28
Gender of operator *(male) dummy)*	75.0	3.0	73.3	3.0	84.0***	3.8	71.4	2.5
Total area owned *(acres)*	3.17	0.20	3.05	0.21	3.54*	0.33	2.98	0.16
General farming experience *(years)*	22.7*	0.97	20.8	1.01	22.7	1.5	21.4	0.8
Age of operator *(years)*	52*	1	50	1	52	1	50	1
Household size *(number of people)*	6.07**	0.16	5.58	0.16	6.38***	0.25	5.66	0.12
Proportion of household that received forecast on:								
Onset of rains *(%)*	87.0*	2.3	81.8	2.6	85.1	3.7	84.1	2.0
Extreme weather occurrence *(%)*	88.0***	2.3	77.8	2.8	88.3*	3.3	81.1	2.1
Member of group currently *(%)*	83.7***	2.6	62.2	3.2	85.1***	3.7	69.0	2.5
Member of group in 2012 *(%)*	30.8***	3.2	14.7	2.4	28.7**	4.5	20.6	2.2
Common source of consumed food (share of frequency of source)								
Own production	0.42***	0.23	0.36	0.22	0.43***	0.20	0.37	0.24
Purchases	0.58***	0.23	0.64	0.22	0.56***	0.19	0.63	0.24
Consumption of own-produced animal source food (ASF) in 2016								
Quantity of eggs produced	439**	147	170	52	775***	318	167	38
Quantity of eggs consumed	271**	107	72	12	413***	225	100	21
Quantity of eggs sold	206	106	79	47	467**	250	49	18
Quantity of milk produced	591	61	501	59	1,065***	140	400	34
Quantity of milk consumed	365	33	378	87	738***	202	270	21
Quantity of milk sold	224	40	229	63	583***	155	128	20
Quantities of crops produced, consumed, and sold								
Maize harvested	2.9*	0.3	4.3	0.9	5.0*	0.9	3.2	0.6
Maize consumed	2.5	0.2	3.0	0.8	3.2	0.4	2.7	0.6
Maize sold	0.6*	0.1	1.1	0.3	1.9***	0.7	0.5	0.1
Sorghum harvested	2.1	0.4	1.5	0.6	2.7*	0.8	1.5	0.4
Sorghum consumed	1.8	0.4	1.3	0.6	2.3	0.8	1.3	0.4
Sorghum sold	0.4*	0.2	0.2	0.1	0.4	0.1	0.2	0.1

*; **; ***Mean values are significantly different between adopters and non-adopters at 10%, 5%, and 1% level

Adopters of CSA consume significantly more of own-produced animal source food (ASF) such as eggs and milk and own-produced multiple-stress tolerant crops. This gave them a slightly superior dietary diversity score. Adopters of improved livestock tended to sell significantly more livestock and livestock products.

In Fig. 3, we further explored HDDS and household food insufficiency. Panel (a) of Fig. 3 shows the distribution of household dietary score classified by adoption of the two CSA technologies. We see from the box plot that adopters of multiple stress-tolerant crops have dietary diversity scores distributed between three and 12, while some households that have adopted neither of the two technologies have dietary scores below two. Households that adopt both technologies have more diverse diets; half of these households have HDDS of eight or more.

From panel (b) we see that households adopting only improved livestock tended to have shorter periods of food insufficiency; 50% of these households experienced a maximum of three months of food insufficiency per year. In contrast, 50% of households not adopting either of the two CSA technologies experienced five or more months of food insufficiency. These trends lend credence to the hypothesis that

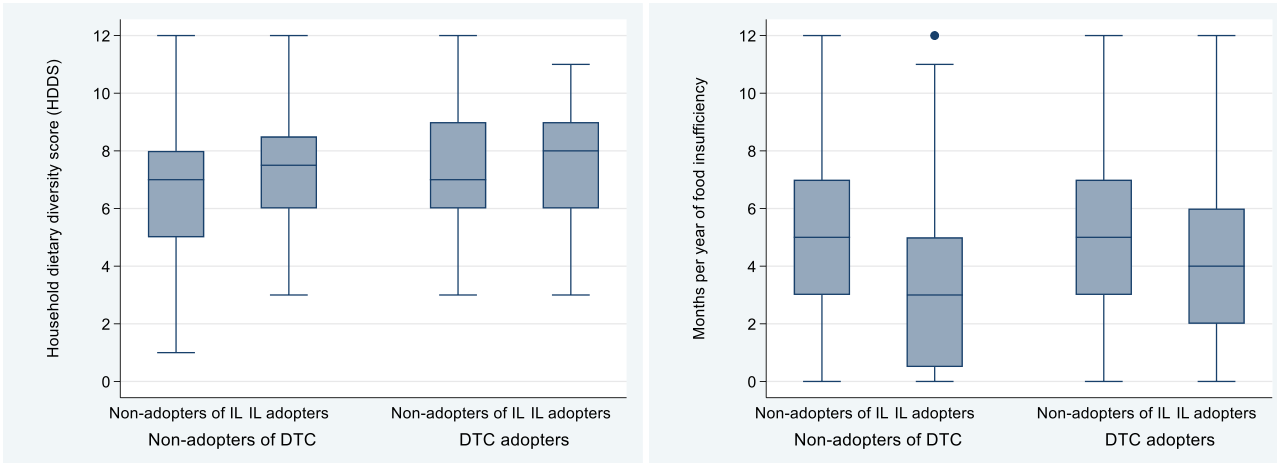

Fig. 3 Box plots of HDDS (panel a) and hunger months (panel b) by adoption of multiple stress-tolerant crops—DTC and improved livestock—IL

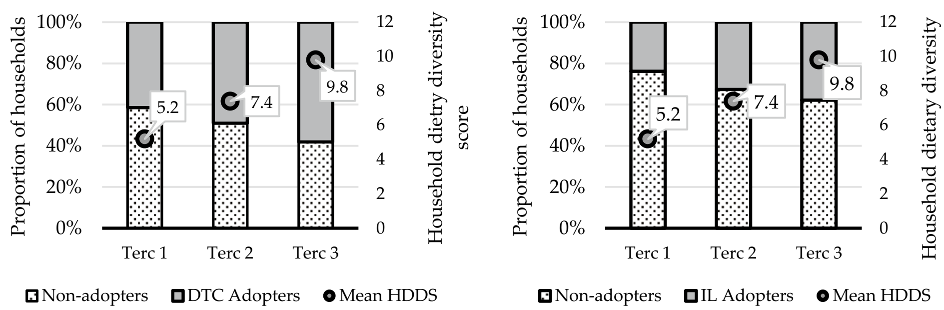

Fig. 4 Adoption of multiple stress-tolerant crops—DTC (panel a) and improved livestock – IL (panel b) by household dietary diversity score terciles

adoption of CSA practices may positively impact food and nutrition security outcomes.

Besides mean comparison in Table 1, we looked at correlation between CSA adoption and HDDS. We see from Fig. 4 that higher adoption rates for both multiple stress tolerant crops (*panel a*) and improved livestock (*panel b*) was associated with higher dietary diversity scores. The third tercile, with a mean HDDS of 9.8 also has the largest proportion of adopters. This is true for adoption of both multiple stress tolerant crops and improved livestock breeds that have 58% and 38% adoption rates respectively, in the third tercile of HDDS.

In Fig. 5 we see a clear negative relationship between adoption of improved livestock and household food insufficiency. Tercile 3, with the highest number of months of household food insufficiency, also had the lowest proportion of adopters at about 9%. There was, however, no consistent relationship between adoption of multiple stress-tolerant crops and household food insufficiency. These relationships are indicative of possible impacts of CSA technologies on household food and nutrition security, which we analyzed using appropriate econometric approaches in the next section.

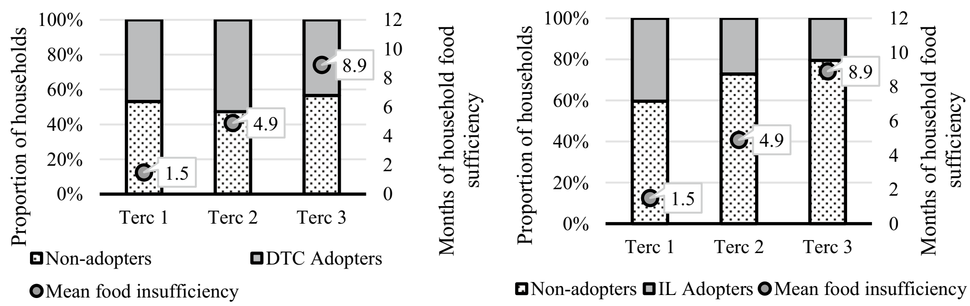

Fig. 5 Adoption of multiple stress-tolerant crops (DTC) (panel a) and improved livestock – IL (panel b) by household food insufficiency terciles

Table 2 Determinants of adoption of multiple stress-tolerant crops and resilient livestock breeds

	Adoption of multiple stress tolerant crops (DTC)		Adoption of resilient livestock breeds (IL)	
	Coefficient	SE	Coefficient	SE
Farming experience	0.008	0.007	0.002	0.009
Livestock rearing experience			-0.008	0.008
Gender of household head (*male dummy*)	0.176	0.163	0.253	0.185
Age of household head	-0.008	0.007	0.011	0.007
Educational status of household head [a]				
Primary	-0.082	0.233	0.168	0.266
Secondary	-0.102	0.266	0.076	0.297
Post-secondary	-0.001	0.370	0.309	0.368
Distance to nearest market	-0.074	0.048	-0.033	0.043
Distance to the nearest road	0.147**	0.063	0.317***	0.067
Lagged group membership	0.373**	0.166	0.296*	0.166
Total land owned (*acres*)	0.020	0.025	-0.021	0.028
Type of weather forecast information received				
Extreme weather occurrence	-0.023	0.244	-0.198	0.231
Onset of rains	-0.020	0.257	-0.156	0.269
Occurrence of pest & diseases	0.038	0.143	-0.225	0.148
Occupation of household head [b]				
Farm wage employment	-0.934**	0.472	-0.366	0.577
Non-farm employment	-0.161	0.219	0.127	0.213
Microenterprise	-0.125	0.195	0.014	0.199
Livestock herd in 2012 (TLU)			0.045**	0.020
Introduction of new crop varieties by others within the village	0.065**	0.028	0.103***	0.035
Frequency in agrovet sourcing by others in the village	-0.011	0.007	-0.010*	0.005
Source of weather/climate information				
Radio	0.465*	0.269	0.379	0.293
Friends and relatives	0.003	0.192	0.199	0.200
Local groups	0.381**	0.179	-0.260	0.194
Vegetation index	-6.631***	1.809		
Constant	1.286*	0.683	-2.484***	0.502
Number of observations		*408*		*424*

3.2 Adoption of multiple stress-tolerant crops and resilient livestock breeds

Table 2 presents results of the probit model that estimates determinants of adoption[1] of the two CSA technologies. Estimation results show that distance from roads and group membership positively and significantly influenced adoption of multiple stress-tolerant crop varieties (DTC). Households located in remote areas that are not exposed to large road networks are likely to focus on farming as a main source of livelihood. This is unlike those near roads that have access to alternative off-farm activities. On the other hand, social groups provide networks through which information is shared and most projects tend to use such outfits as entry points when introducing innovations. Hence the positive effect observed here. Indeed, sharing of weather-related information via local groups had a positive and significant effect on adoption. Farm wage employment had a negative and significant influence on adoption of multiple stress-tolerant crop varieties. Households engaging in farm wage employment tend to have limited or no access to land of their own, which could be limiting their capacity to experiment with new crop varieties. We also note the

[1] Note that, determinants of adoption of multiple stress-tolerant crops and resilient livestock breeds can be estimated directly from the endogenous treatment effect model as the selection equation in respective model. In the interest of saving space we only show here the adoption results separately and only selected results of treatment effects. The full results of the joint estimation of adoption and outcome are reported in Tables 5, 6, 7 and 8 in the Appendix. The full results are available upon request.

Table 3 Effects of adoption of CSA technologies on household dietary diversity and food insufficiency

	Multiple stress-tolerant crops			Resilient livestock breeds		
	PSM (NNM)	PSM (KBM)	Endogenous treatment	PSM (NNM)	PSM (KBM)	Endogenous treatment
Household dietary diversity	0.71** (0.327)	0.52** (0.231)	2.651*** (0.616)	0.85*** (0.337)	0.55*** (0.244)	2.622*** (0.702)
ρ_{u_2-DTC,u_1-HDDS}			-0.468** (0.182)			
ρ_{u_2-IL,u_1-HDDS}						-0.439** (0.192)
Household food insufficiency	-1.00** (0.492)	-0.60 (0.401)	-3.612** (1.713)	-1.27*** (0.517)	-1.01*** (0.416)	-4.625*** (1.348)
ρ_{u_2-DTC,u_1-HMS}			0.623*** (0.138)			
ρ_{u_2-IL,u_1-HMS}						0.502** (0.200)

Robust standard errors are reported in parentheses

*; **; ***represents statistical significance at 10%, 5%, and 1% levels respectively

positive and significant role of peer influence and information since the introduction of new crop varieties by other households within the village tend to have positive and significant influence on adoption of multiple stress-tolerant crops. As expected, we found that adoption of multiple stress-tolerant crops is associated with places that have poor vegetation index,[2] an indication of climatic stress. Healthy vegetation has the highest index, which tends towards + 1.

For adoption of resilient livestock breeds, we see from Table 2 that households that already kept some form of livestock prior to project interventions were more likely to adopt the improved livestock breeds. This is indicative of their reliance on livestock as a source of livelihood and hence their investment in protecting such livelihoods. Similar to multiple stress-tolerant crops, adoption of resilient livestock breeds is also positively associated with residence away from roads and group membership, as well as peer influence.

3.3 Treatment effects of CSA technologies

Summary results from the estimation of treatment effects of CSA technologies are shown in Table 3 (for detailed results refer to the Appendix). In columns 1 and 2, we present treatment effects of adoption of multiple stress-tolerant crop varieties on dietary diversity and food insufficiency based on a PSM[3] approach. Similar results for the adoption of resilient livestock breeds are in columns 4 and 5. The matching procedure was conducted with STATA 17 software, following steps described by Leuven and Sianesi (2003). Finally, we show results of the endogenous treatment effect modelling of the two technologies in columns 3 and 6.

3.3.1 Treatment effect of multiple stress-tolerant crop varieties

Overall, the two technologies are shown to significantly increase household dietary diversity (HDDS) while reducing household food insufficiency. Using the PSM approach, we found that uptake of multiple stress-tolerant crops increases household dietary diversity (HDDS) by 0.52 to 0.71 point. This represents an increase of between 8−11 percent in HDDS, relative to the average HDDS of 6.8 for non-adopters. Adoption of multiple stress-tolerant crops was also seen to reduce household food insufficiency by 0.6–1 month. This is equivalent to a 13–21% reduction in household food insufficiency, relative to a food insufficiency period for non-adopters of 4.8 months.

However, in the presence of hidden bias, matching techniques do not provide efficient estimates of impact. We therefore augmented the matching approach with an endogenous treatment effect procedure that accounts for both observable and unobservable sources of bias. We applied this estimation on a comparable sample of adopters and non-adopters obtained via PSM. The endogenous treatment effect estimation shows that adoption of multiple stress-tolerant crops significantly increases dietary diversity score by 2.65 points, a 40% increase in dietary diversity relative to average dietary diversity score for non-adopters of 6.8. This estimate is higher than the 8–11% from the PSM estimator, indicating a negative selection bias (i.e., households with below average dietary diversity may have been targeted/encouraged/self-selected into adoption of multiple stress-tolerant crop varieties, leading to underestimation of impacts in the absence of relevant selection correction model). We also confirmed endogeneity of adoption in this model (significance of the

[2] The normalized difference vegetation index (NDVI) is a composite index ranging from -1(deep water), 0 (no greenness, e.g. snow, rocks, and sand) to + 1(maximum greenness). Healthy vegetation has the highest index, which tends towards + 1 (Lillesand et al., 2015).

[3] Average treatment effects on the treated (ATT) based on PSM approach for adoption of the 2 CSA technologies were estimated using nearest neighbour matching (NNM) and kernel-based matching (KBM) methods, while imposing the common support condition to ensure proper matching.

correlation term (ρ_{u_2-DTC,u_1-HDDS}) and therefore appropriateness of the model in addressing this challenge.

We also found that adoption of multiple stress-tolerant crops significantly reduces household food insufficiency. Adoption of these crops reduces months of food insufficiency by 3.6 months, holding all other factors constant. This is equivalent to 75% reduction in household food insufficiency relative to an average food insufficiency period of 4.8 months for non-adopters of multiple stress-tolerant crops. This is a huge difference from the 21% reduction realized via PSM, confirming again substantial negative selection bias. Again, endogeneity of adoption and therefore appropriateness of the model was confirmed.

3.3.2 Treatment effects of resilient livestock breeds

Columns 4–6 of Table 3 presents treatment effects of adoption of resilient livestock breeds. Based on the PSM approach we found that uptake of resilient livestock breeds increases HDDS by 8–12 percent, considering an average dietary diversity of 6.9 for non-adopters of resilient livestock breeds. Adoption also reduced household food insufficiency by 1.01–1.27 months – equivalent to 20–25% reduction compared to 5.08 months of food insufficiency for non-adopters. On the other hand, the endogenous treatment effect estimation reveals that adoption of improved livestock breeds increases household dietary diversity score by 2.62 points, an equivalent of 38% increase relative to average dietary diversity score of 6.9 for non-adopters of improved livestock breeds. Again, the estimated impact was substantially larger than results of the PSM estimator (8–12%), indicating selection bias, which is also evident from the significance of correlation coefficient, ρ_{u_2-IL,u_1-HDDS}.

Finally, we found that adoption of resilient livestock breeds reduces the period of household food insufficiency by about 4.6 months per year. Relative to 5.1 months of food insufficiency for non-adopters, this represents a huge impact – a 90% reduction in the period of household food insufficiency. This impact is higher than that estimated for multiple stress-tolerant crops.

3.3.3 Validity of the matching assumption

PSM estimates are valid subject to two conditions: (i) there is no systematic farmer heterogeneity due to unobservable effects and (ii) balancing of covariates is achieved (Caliendo & Kopeinig, 2008; Dehejia & Wahba, 2002). Since PSM analysis addresses selection bias due to observable factors, we need to test for potential hidden bias due to *unobservable* factors. We used Rosenbaum bounds to test for potential hidden bias (Rosenbaum, 2002). Assuming two individuals have the same observed covariates z (*as implied by the matching procedure*), the two observations would differ in their odds of adopting CSA technologies only by the difference in unobserved covariates, which is measured by the parameter $\boldsymbol{\Gamma}$. The test procedure involves changing the level of $\boldsymbol{\Gamma}$ and deriving the bounds on the significance levels of the ATT under the assumption of endogenous self-selection into adoption. This allows for identification of the critical levels of $\boldsymbol{\Gamma}$ at which the estimated ATT would become insignificant.

Results of this test are shown in Table 4. Using the example of impacts of multiple stress-tolerant crops on household food insufficiency, the critical values for hidden bias ($\boldsymbol{\Gamma}$) are 1.20–1.25 for both NNM and KBM. The lowest value of Γ =1.2 implies that individuals that have the same z-vector would have to differ in their odds of adopting multiple stress-tolerant crops by 20% to render the ATT for household food insufficiency insignificant. A difference in odds of adoption of 20% due to unobserved factors is relatively low and may not inspire confidence in the estimated treatment effects. It implies that hidden bias can easily invalidate some of our findings of significant treatment effects. Hence the use of a complementary endogenous treatment effect approach.

We also conducted a balancing test to determine whether matching was able to reduce bias by eliminating differences

Table 4 Indicators of covariate balancing before and after matching

	Impact of multiple stress-tolerant crops		*Impact of improved livestock breeds*	
	household dietary diversity	*household food insufficiency*	*household dietary diversity*	*household food insufficiency*
Median absolute bias before matching	14.3	18.1	28.8	28.8
Median absolute bias after matching	5.3	4.5	12.4	7.0
% bias reduction	62.9	75.1	56.9	75.7
Pseudo R (unmatched)	0.17	0.19	0.21	0.23
Pseudo R (matched)	0.03	0.05	0.05	0.06
p-value of LR (unmatched)	0.000	0.000	0.000	0.000
p-value of LR (matched)	0.519	0.207	0.621	0.370
Critical level of hidden bias ($\boldsymbol{\Gamma}$)	1.40–1.45	1.20–1.25	1.45–1.50	1.45–1.50

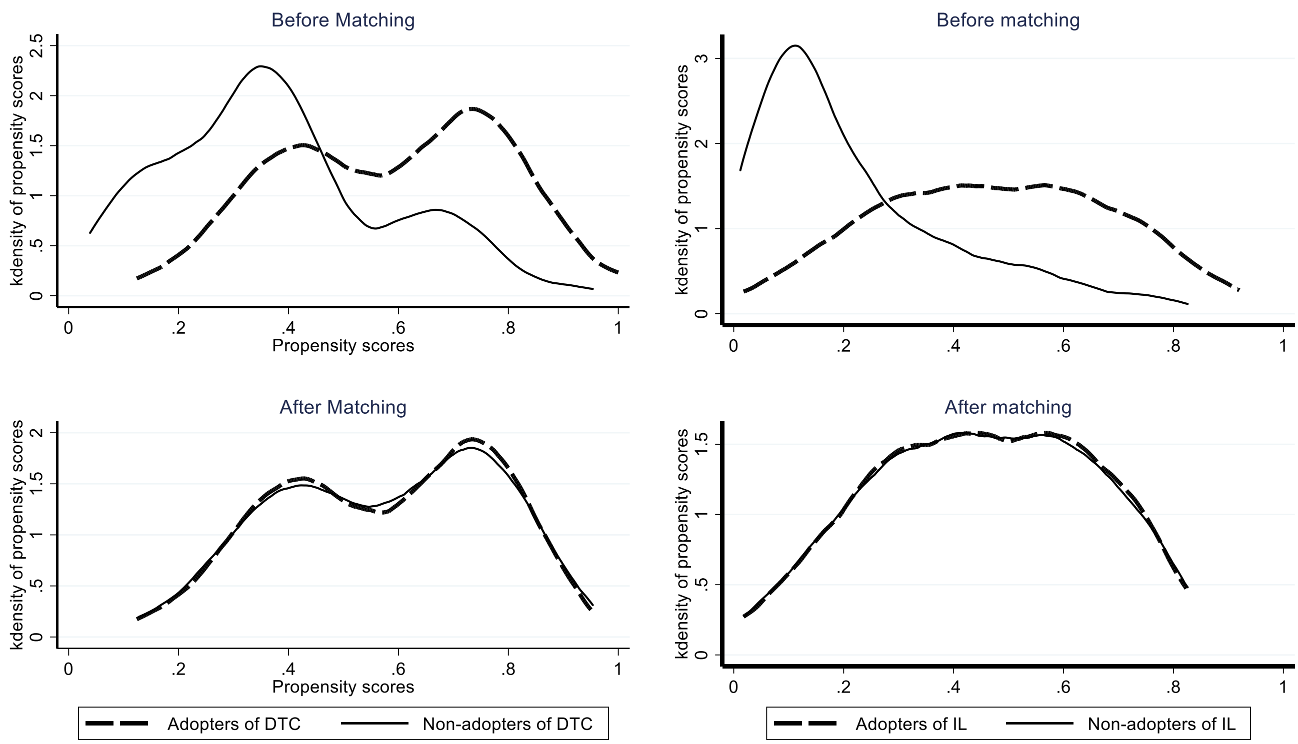

Fig. 6 Distribution of propensity scores before (upper panels) and after (lower panels) matching for sub-samples of adopters and non-adopters of multiple stress-tolerant crops (DTC) and improved livestock (IL)

in the covariates (Rosenbaum, 2002). Balancing test reveals substantial reduction in bias achieved via statistical matching (see Table 4), underlining the fact that systematic differences due to observable factors have been eliminated via matching.

We also see from Fig. 6 that the distribution of propensity scores is similar between adopters and non-adopters *after matching*. This is true for both adoption of multiple stress-tolerant crops and improved livestock and confirms the efficacy of the matching approach in achieving similarity between adopters and non-adopters.

Both distributions show considerable overlap in common support. Among adopters of multiple stress-tolerant crops, the predicted propensity scores range between 0.124 and 1 with a mean of 0.587, while non-adopters have predicted propensity scores ranging between 0.039 and 0.957 with a mean of 0.378. The common support requirement is therefore satisfied in the region of (0.124, 0.957) with a loss of only five treated observations. For adoption of improved livestock, the predicted propensity score for adopters range between 0.043 and 0.887 with a mean of 0.489, while distribution for non-adopters range between 0.016 and 0.894 with a mean of 0.220. The common support requirement for adoption of improved livestock is satisfied in the region of (0.043, 0.887) with a loss of six treated observations.

Based on the estimated impacts, we conclude that uptake of climate-smart interventions had positive and significant impact on food security. The estimated impact appears to be largely coming from increased production of foods. As illustrated in Table 1, while purchases remain the largest source of food for households, adopters of the two CSA technologies rely significantly more on own-produced food sources than non-adopters, indicating the relative contribution of own production to food security among adopters. These findings are consistent with Teklewold et al. (2019) who showed that adoption of climate smart innovations increase dietary diversity while improving calorie and protein availability at household level, especially when innovations are adopted in combination. Several other studies have also shown that CSA technologies have major impacts on crop yields (Amadu et al., 2020; Martey et al., 2020), underscoring the potential impact of CSA on food security via own production.

Additionally, the significantly large impact on resilient livestock breeds on household food insufficiency can be attributed to sale of livestock products to bridge the hunger gap. Table 1 shows that adopters of livestock breeds sell significantly large quantities of animal source food products, proceeds of which could be used to purchase food during lean periods. This is consistent with Jodlowski et al. (2016) who showed that livestock ownership improves dietary diversity through direct consumption of farm-produced animal products and through increased consumption expenditures.

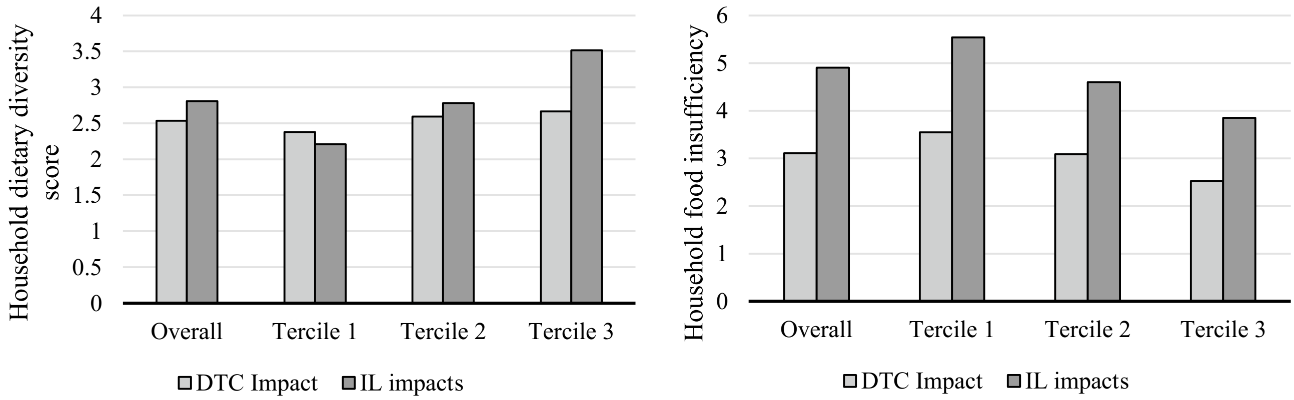

Fig. 7 Heterogeneity of treatment effects by dietary diversity and food insufficiency terciles

3.4 Heterogeneity in treatment effect

To conclude, we estimated the average treatment effect on the treated (ATT) – i.e., impact of adoption on those who have adopted the two CSA technologies. We also look at how these effects vary across various sub-samples of adopters and by key control variables. To achieve this, we first estimated an endogenous treatment effect model that allows for interaction between treatment variable (*adoption*) and each covariate. We then predicted for each observation the potential outcome means (*POMs*) – "the expected value of food security outcome that would have been observed if everyone was assigned to treatment and control" (StataCorp, 2017). ATT for each observation is then estimated as the difference between POMs

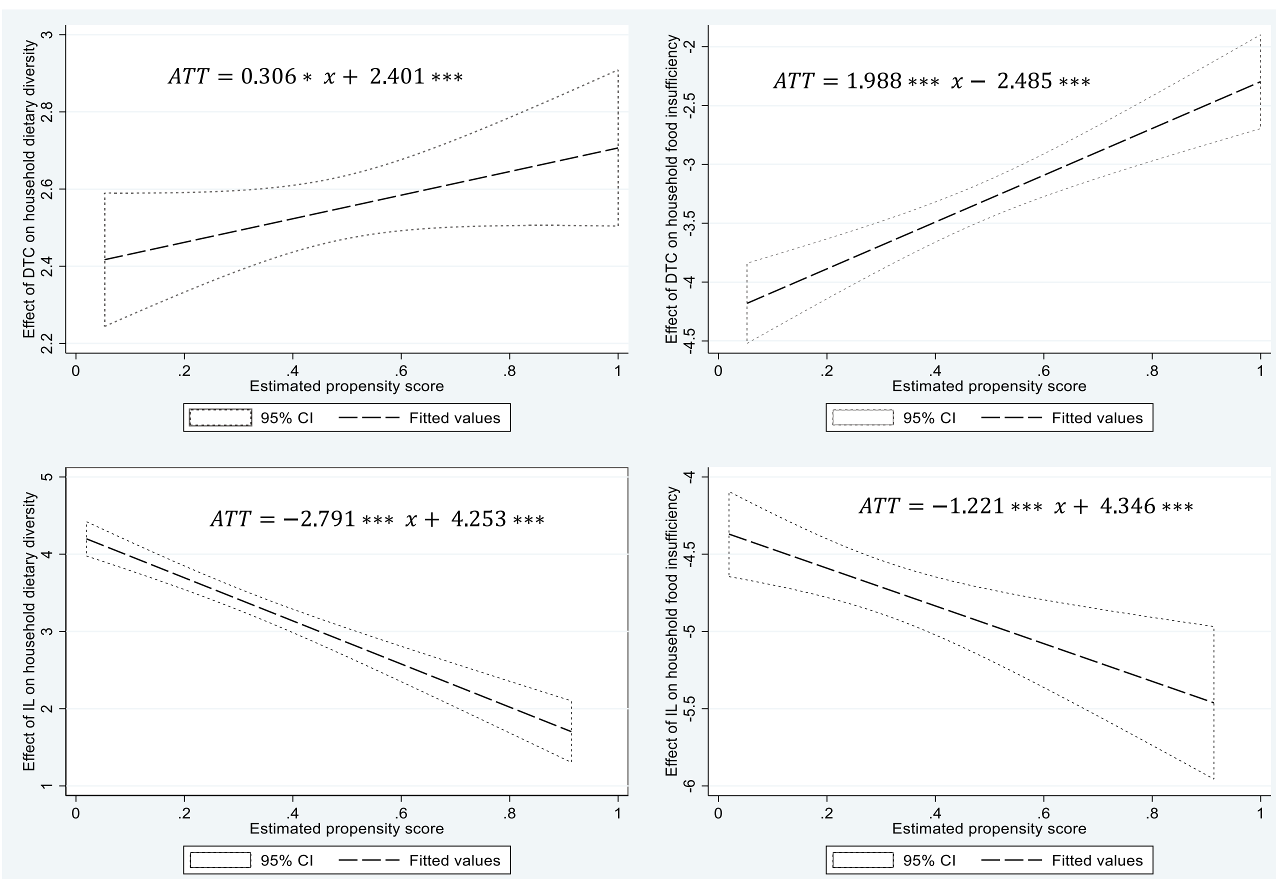

Fig. 8 Heterogeneity of treatment effects over propensity scores

for treatment and control levels. Following this process, we predict ATT for the overall sample and the sub-samples.

On average, adopters of resilient livestock breeds realized greater impacts than adopters of multiple stress-tolerant crops. This is true for increases in dietary diversity and reduction in household food insufficiency with an even bigger difference for reduced effect on food insufficiency (see Fig. 7). This could be attributed to increased diversity that livestock-derived foods bring into diets (Taruvinga et al., 2013; Workicho et al., 2016) compared to adoption of multi stress-tolerant crops that may go towards augmenting existing starch-based components of diets. Moreover, livestock can be sold during lean periods when there are fewer crop-based food products thus enabling households to bridge the hunger gap and minimize periods of food insufficiency.

3.4.1 Heterogeneity over food security terciles

Sub-sample summaries of ATT show that these impacts also vary across households, with adopters in the third tercile realizing the largest increase in household dietary diversity. This was true for both adoption of multiple stress-tolerant crops and resilient livestock breeds. On the other hand, households in the 1st tercile of household food insufficiency distribution (the group with shortest period of food insufficiency) appear to have benefited most from adoption of multiple stress-tolerant crops and resilient livestock breeds. Moreover, adoption of improved livestock appears to have been more effective in reducing household food insufficiency across all terciles. These findings are consistent with Megersa et al. (2014), who show that livestock diversification is more effective in enhancing food security especially among pastoralists.

3.4.2 Heterogeneity over propensity scores

Following Verhofstadt and Maertens (2015) and Wossen et al. (2017), we also evaluated how dietary diversity and food insufficiency effects vary over estimated propensity scores (PS) and socio-demographic variables. These are illustrated graphically in Figs. 8 to 11. The distribution plots in these figures are obtained via two-way plots of the linear or quadratic fit of the relationship between the ATTs

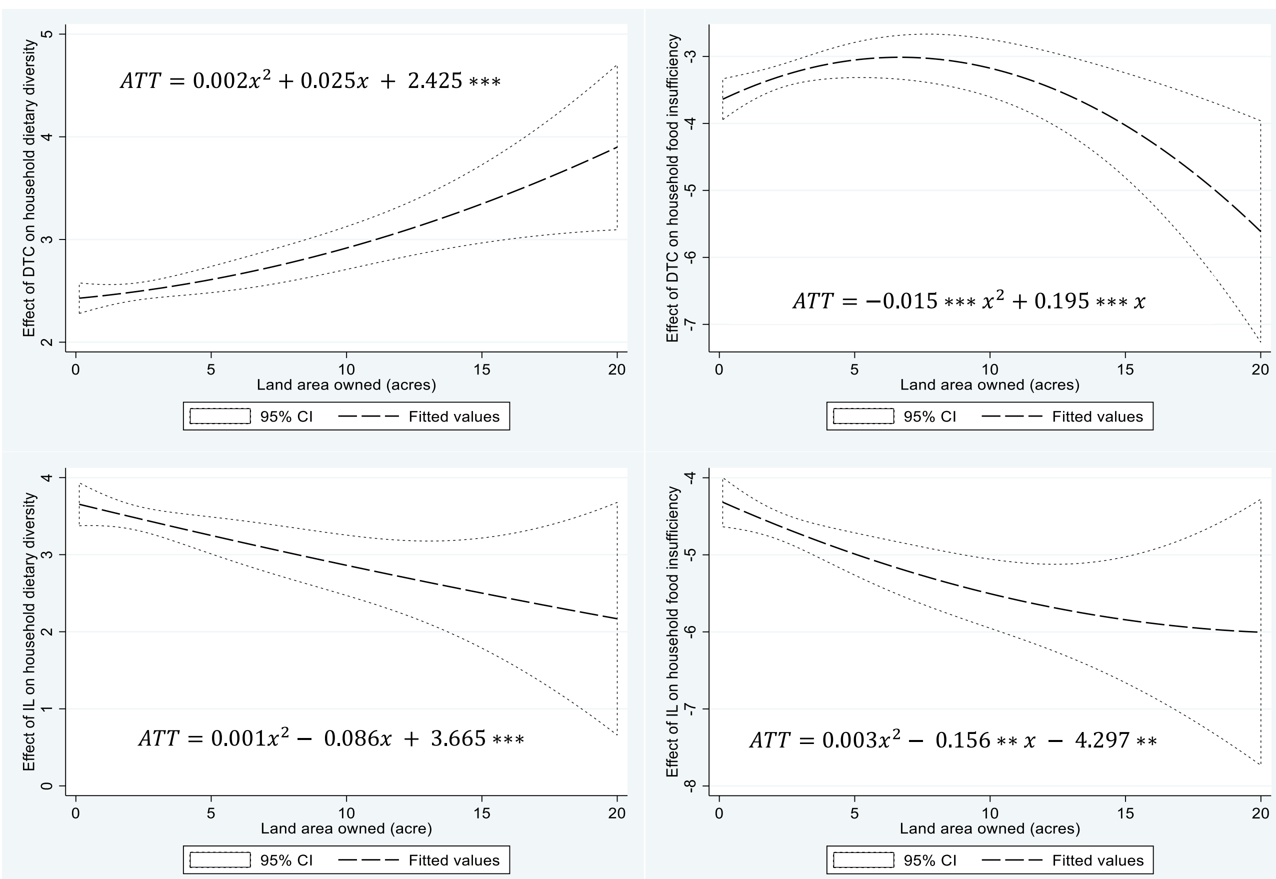

Fig. 9 Heterogeneity of treatment effects over land ownership

and heterogeneity variable of interest. In Fig. 8, we see that ATT on dietary diversity vary significantly with PS. The slope is also positive, indicating that adoption of multiple stress-tolerant crops is more effective in increasing dietary diversity among households that are more likely to adopt respective crops (i.e., households that would gain the most from adoption are the ones who are more likely to adopt). The slope of ATT on household food insufficiency is also a positive slope and highly significant. We also see from the lower panel of Fig. 8 that adoption of resilient livestock breeds is most effective in enhancing dietary diversity among households that are least likely to adopt, while it is less effective in increasing dietary diversity for households that are more likely to adopt. On the other hand, adoption of resilient livestock breeds is more effective in reducing food insufficiency among households that are more likely to adopt respective livestock breeds.

3.4.3 Heterogeneity over land ownership

Illustrations in Fig. 9 show that treatment effects of multiple stress-tolerant crops on dietary diversity are larger for households with larger landholdings. However, this effect of land was not significant. We also see that food insufficiency reducing effects of these crops reduce slightly with landholdings up to a threshold of about six acres and thereafter increase with landholdings. This implies that there is a critical level of land ownership above which adoption of multiple stress-tolerant crops begin to impact on household food insufficiency. The lower panel of Fig. 9 shows that adoption of resilient livestock breeds is more effective in increasing dietary diversity for households with smaller landholdings. This effect is, however, insignificant. On the other hand, food insufficiency reducing effects of improved livestock breeds is more pronounced for households with large landholdings. Given the average landholding of three acres, it is evident that larger impacts of the two CSA technologies will be limited to few households.

3.4.4 Heterogeneity over socio-demographic variables

Finally, we also looked at how treatment effects vary over educational level and age of household head. Figure 10 shows that

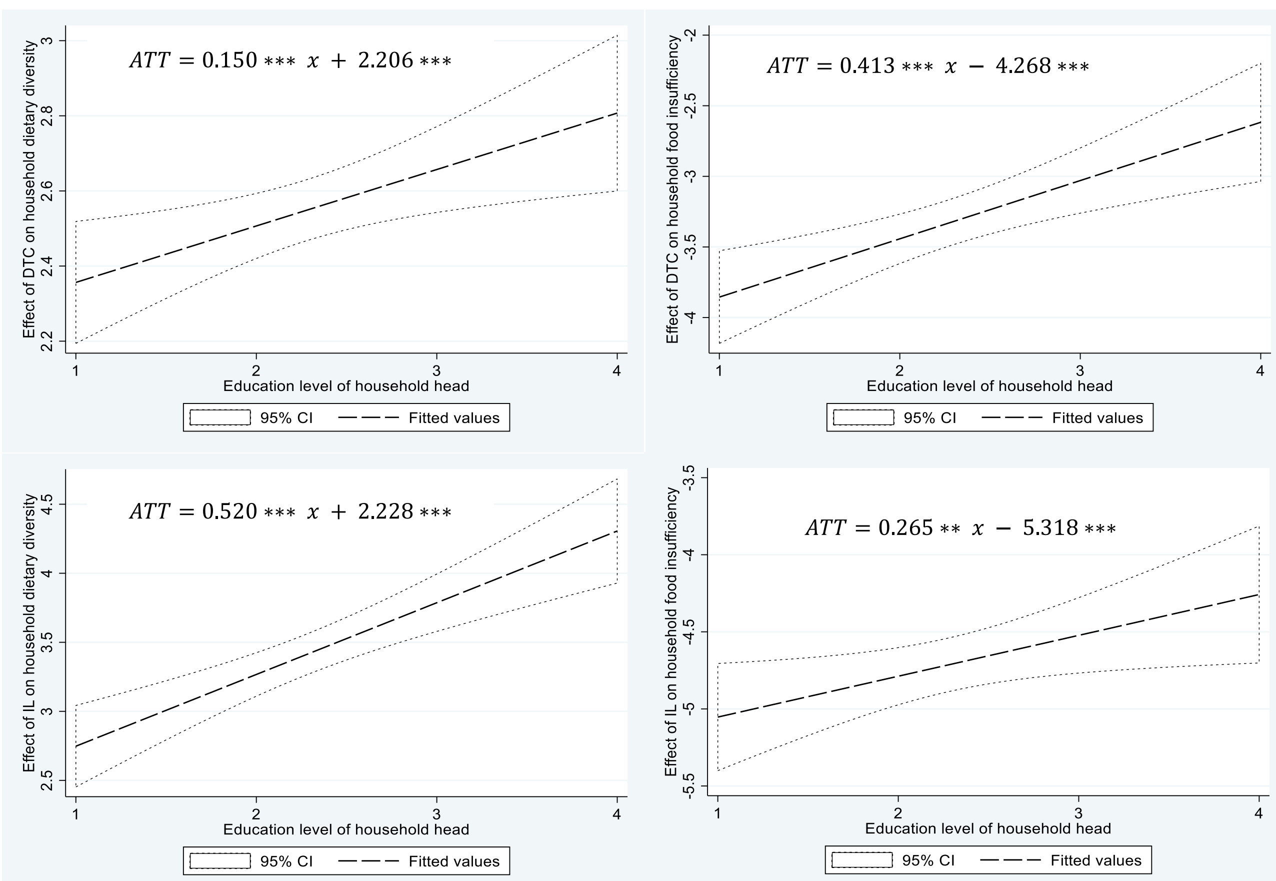

Fig. 10 Heterogeneity of treatment effects over education level

adoption of multiple stress-tolerant crops is more effective in enhancing dietary diversity for households whose heads are more educated. However, the food insufficiency reducing effect of multiple stress-tolerant crops is more pronounced for households with less education. Similarly, we see that the treatment effect of adoption of improved livestock breeds on dietary diversity increases with education while food insufficiency reducing effects are larger for households headed by the less educated, probably due to diverse livelihood alternatives that better education may offer.

The estimated treatment effects also exhibit heterogeneity over age of the household head as illustrated by Fig. 11. Treatment effect of multiple stress-tolerant crops on household dietary diversity increases with age of household head but at a decreasing rate. This continues up to a threshold of 70 years of age when the effects begin to reduce. These treatment effects of resilient livestock breed on dietary diversity are, however, unaffected by age of household head. We also noticed that the food insufficiency reducing effects of multiple stress-tolerant crops are unaffected by age. Finally, food insufficiency reducing effect of resilient livestock breeds is more pronounced for households with younger and much older heads.

Overall, our heterogeneity analysis reveals that adoption of multiple stress-tolerant crops is more effective in enhancing dietary diversity among households that have large landholdings and whose heads are more educated and of advanced age. With respect to household food insufficiency, we noted that food insufficiency reducing effects of multiple stress-tolerant crop are significantly larger for households that have larger landholdings (at least five acres), and households with less educated heads. Smaller landholdings and higher levels of education are therefore hindrances to the effectiveness of multiple stress-tolerant crops in reducing food insufficiency.

Compared to multiple stress tolerant crops, we find that adoption of resilient livestock is more effective in increasing

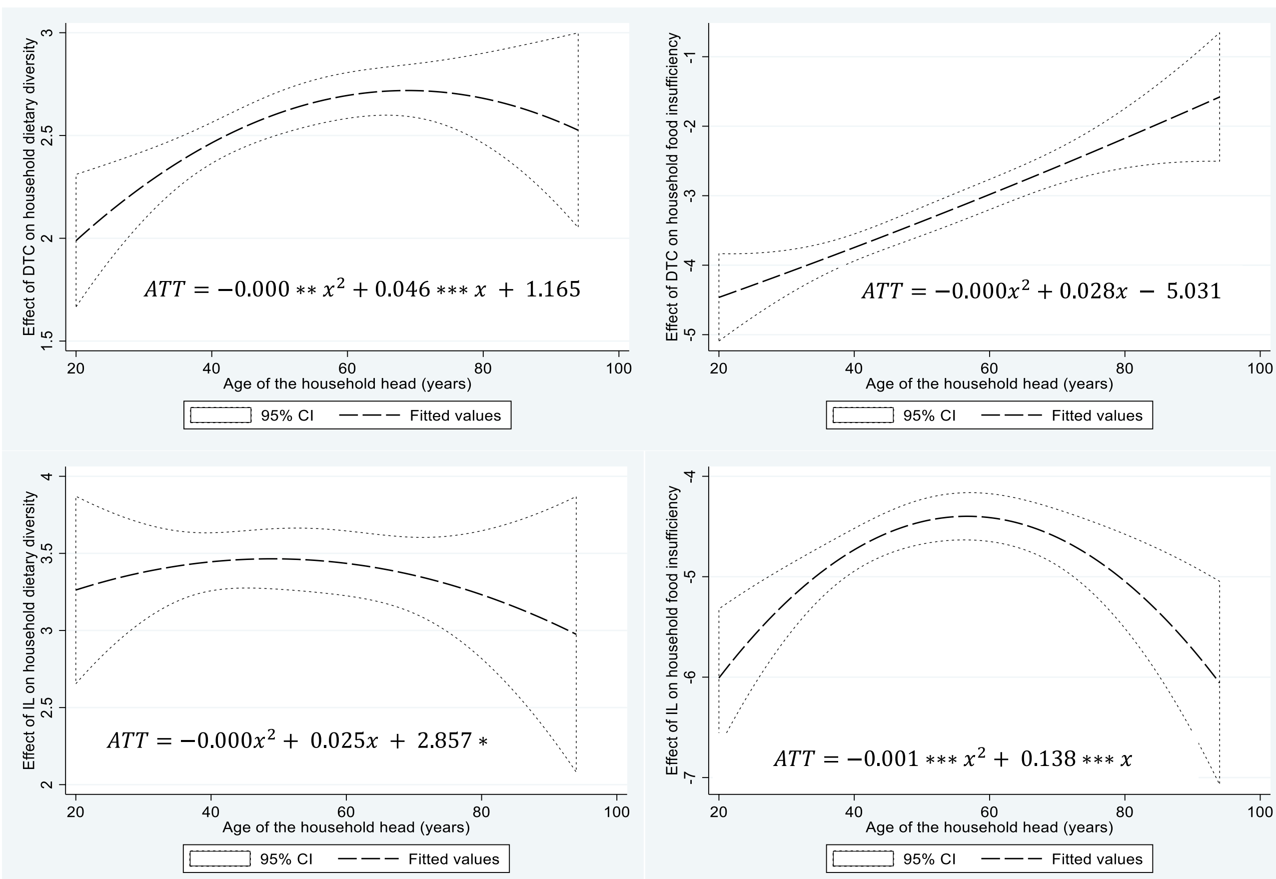

Fig. 11 Heterogeneity of treatment effects over age of household head

dietary diversity among households who are *less likely to adopt*. Notably, these households have smaller landholdings but are more educated. It therefore appears that small landholding is a hindrance to the effectiveness of resilient livestock breeds in increasing dietary diversity. Moreover, higher education may imply reliance on non-farm sources of livelihood, causing these households to invest less in crop-based mitigation against food insecurity risks. Mutisya et al. (2016) also find that education attainment had a positive and significant effect on household food security, especially among urban households. This is mainly realised through access to information on best production practices, nutrition and sanitation as well as better decision making and hence increased efficiency in production (Bashir & Schilizzi, 2013).

Finally, we also see that adoption of resilient livestock breeds is more effective in reducing food insufficiency among those who are *more likely to adopt*, again indicating appropriate targeting of interventions. These households tend to have larger landholdings, have either younger or much older heads who also happen to have low levels of education, again confirming that adoption of resilient livestock tends to favour households with large landholdings.

4 Conclusions

Using household data from the Nyando Basin of Western Kenya, this study sought to establish the impact of uptake of CSA technologies on household food and nutrition security. Two measures of food and nutrition security, household dietary diversity and household food insufficiency, were used. For robust results, the study used two quasi-experimental approaches: Propensity Score Matching and endogenous treatment effect. Overall, the results show that adoption of CSA technologies is very effective in improving household food and nutrition outcomes. Adoption of multiple stress-tolerant crops improved household dietary diversity by 40% and reduced household food insufficiency by a very large 75%. Adoption of improved and resilient livestock breeds improved household dietary diversity by 38% while reducing household food insufficiency by 90%.

We also found that resilient livestock breeds are more effective in reducing food insufficiency among households at lower distribution of insufficiency while at the higher distribution of dietary diversity, multiple stress-tolerant crops were the superior intervention. This shows that adoption of resilient livestock breeds has superior redistribution effects than multiple stress tolerant crops.

The links between multiple stress-tolerant crop varieties and livestock breeds to food and nutrition security are clear. These tolerant crop varieties minimise the risk of crop failure and increase the crop yields. This increases food availability to households. The fact that the farmers are also diversifying crop production improves food varieties available to households, thereby enhancing dietary diversity. Similarly, tolerant livestock breeds improve livestock production, yielding direct nutritional benefits from livestock derived food such as milk, eggs, and meat. It is also important to note that households may sell excess farm produce arising from these tolerant crop varieties and livestock breeds to be able to purchase food products which are not produced on-farm. These findings are consistent with those of previous studies on impact of improved agricultural technologies and innovations on household welfare (Amare et al., 2012; Asfaw et al., 2012; Kassie et al., 2011; Kiiza & Pederson, 2012; Simtowe et al., 2019).

To obtain maximum effects on household dietary diversity from the adoption of multiple stress-tolerant crops, promotion efforts should target households with *large landholdings*, households with *more educated heads* and *heads that are young to middle age*. For greater effects on reducing food insufficiency, efforts to promote multiple stress tolerant crops should target households with more land but less educated heads. Effectiveness of resilient livestock on dietary diversity and food insufficiency is enhanced by targeting households with either *young or much older heads*. Moreover, households headed by heads with *low levels of education* would also benefit while *small landholdings* would limit effectiveness. From these analyses, it is evident that small landholding is a major impediment to the uptake of both types of CSA technology, thereby, in practice, compromising the effect of these technologies on household food security. Policies and approaches aimed at promoting the CSA technologies should take cognizance of these peculiarities among target groups if interventions are to deliver the anticipated impacts. For example, families may be encouraged to consolidate their pieces of land to take advantage of larger-scale operations.

Appendix

Table 5 Adoption and impacts of multiple stress-tolerant crops on household dietary diversity

	Household dietary diversity		Adoption of DTC		Log household income/AE	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	-0.004	0.010	-0.006	0.007	-0.002	0.003
Educational status of household head[a]						
Primary	-0.744*	0.448	-0.075	0.225	0.124	0.182
Secondary	-0.652	0.565	-0.098	0.265	0.229	0.211
Post-secondary	-0.454	0.722	0.061	0.354	0.485**	0.246
Total land owned (*acres*)	-0.075	0.048	0.016	0.024	0.024*	0.013
Main source of livelihood[b]						
Livestock production	0.167*	0.086			-0.023	0.059
Crop production	0.202**	0.083			-0.022	0.058
Off-farm activity	0.177**	0.074			-0.000	0.057
Occupation of household head						
Farm wage employment	1.461	0.900	-0.978**	0.450	0.329	0.200
Non-farm employment	-0.164	0.393	-0.159	0.221	0.094	0.121
Microenterprise	0.319	0.397	-0.110	0.193	0.151	0.130
Gender of household head (*male dummy*)	-0.583*	0.329	0.158	0.162	0.043	0.126
Household size	0.201***	0.073			-0.082***	0.022
Distance to nearest market	0.042	0.086	-0.078*	0.045	0.074***	0.022
Presence of infant	-0.585**	0.237				
Type of weather forecast information received						
Extreme weather occurrence	1.051***	0.388	-0.055	0.240		
Onset of rains	-0.613	0.418	-0.019	0.247		
Occurrence of pest & diseases	-0.587***	0.221	0.021	0.140		
Vegetation index	5.156*	2.924	-6.963***	1.946		
Location variables[c]						
Kaplelartet	1.671**	0.711				
Kapsorok	2.360***	0.565				
NE Nyakach	0.770**	0.378				
Pap Onditi	1.509***	0.552				
Soin	0.957	0.604				
Soliat	1.803***	0.696				
Log household income PAE	1.553**	0.618				
Adoption of DTC	**2.651*****	**0.616**				
Farming experience			0.008	0.005		
Distance to the nearest road			0.172***	0.057	-0.150***	0.027
Lagged group membership			0.369**	0.150	-0.239**	0.099
Introduction of new crop varieties by others within the village			0.067***	0.025		
Frequency in agrovet sourcing by others in the village			-0.012*	0.007		
Source of weather/climate information						
Radio			0.481**	0.214		
Friends and relatives			-0.069	0.163		
Local groups			0.313*	0.163		
Log asset index 2012					0.113***	0.039
Constant	-15.017**	7.215	1.313*	0.731	10.893***	0.648
ρ_{u_2-DTC,u_1-HDDS}					-0.640***	0.106
$\rho_{\varepsilon-lnincome,u_1-HDDS}$					-0.548***	0.158
$\rho_{u_2-DTC,\varepsilon-lnincome}$					0.161**	0.068
Number of observations						*408*

*; **; ***Significant at the 10%, 5%, and 1% level, respectively

[a]Base level of education is no education

[b]Reference occupation is farming (crop/livestock)

[c]Reference location is East Jimo

Table 6 Adoption and impacts of multiple stress-tolerant crops on household food insufficiency

	Hunger months		Adoption of DTC		Log household income PAE	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	0.009	0.016	-0.011*	0.007	-0.002	0.003
Educational status of household head[a]						
Primary	-0.000	0.804	-0.081	0.228	0.117	0.182
Secondary	-0.209	0.938	-0.068	0.262	0.223	0.211
Post-secondary	-0.122	1.163	0.057	0.375	0.474*	0.246
Total land owned (*acres*)	-0.008	0.082	0.018	0.023	0.024*	0.013
Main source of livelihood						
Livestock production	-0.251	0.235			-0.023	0.059
Crop production	-0.288	0.230			-0.022	0.058
Off-farm activity	-0.145	0.223			0.000	0.057
Occupation of household head[b]						
Farm wage employment	-2.129*	1.215	-0.859*	0.462	0.333*	0.202
Non-farm employment	-0.298	0.659	-0.168	0.218	0.091	0.122
Microenterprise	-0.409	0.583	-0.097	0.191	0.148	0.130
Gender of household head (*male dummy*)	0.425	0.539	0.197	0.154	0.046	0.125
Household size	-0.147	0.128			-0.084***	0.022
Distance to nearest market	-0.061	0.144	-0.049	0.051	0.072***	0.022
Presence of infant	-0.081	0.385				
Type of weather forecast information received						
Extreme weather occurrence	-0.106	0.611	-0.025	0.240		
Onset of rains	-0.278	0.574	0.041	0.232		
Occurrence of pest & diseases	-0.229	0.366	-0.024	0.140		
Vegetation index	-4.794	5.141	-5.746***	1.629		
Location variables[c]						
Kaplelartet	-4.049***	1.229				
Kapsorok	-2.709**	1.054				
NE Nyakach	0.167	0.624				
Pap Onditi	-1.426	0.967				
Soin	-1.962	1.334				
Soliat	-2.909**	1.319				
Log household income PAE	-1.572	1.148				
Adoption of DTC	**-3.612****	**1.713**				
Farming experience			0.013**	0.006		
Distance to the nearest road			0.107*	0.064	-0.150***	0.027
Lagged group membership			0.435***	0.149	-0.185	0.117
Introduction of new crop varieties by others within the village			0.053**	0.026		
Frequency in agrovet sourcing by others in the village			-0.009	0.007		
Source of weather/climate information						
Radio			0.404*	0.241		
Local groups			0.160	0.212		
Log asset index 2012					0.120***	0.043
Constant	29.133**	13.742	1.159*	0.630	10.912***	0.646
$\rho_{u_2-DTC,u_1-Hungermonth}$					0.582***	0.217
$\rho_{\varepsilon-lnincome,u_1-Hungermonth}$					0.531***	0.193
$\rho_{u_2-DTC,\varepsilon-lnincome}$					0.183**	0.072
Number of observations						*408*

*; **; ***Significant at the 10%, 5%, and 1% level, respectively

[a]Base level of education is no education

[b]Reference occupation is farming (crop/livestock)

[c]Reference location is East Jimo

Table 7 Adoption and impacts of resilient livestock breeds on household dietary diversity

	Household dietary diversity		Adoption of improved livestock		Log household income PAE	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	-0.017*	0.009	0.008	0.007	-0.001	0.003
Educational status of household head[a]						
Primary	-1.065***	0.403	0.102	0.252	0.144	0.177
Secondary	-0.994*	0.527	0.001	0.286	0.261	0.208
Post-secondary	-0.835	0.643	0.332	0.339	0.402	0.251
Total land owned (*acres*)	-0.022	0.043	-0.022	0.027	0.019	0.014
Main source of livelihood						
Livestock production	0.128	0.097			-0.022	0.067
Crop production	0.200**	0.094			-0.030	0.066
Off-farm activity	0.179**	0.086			-0.011	0.065
Occupation of household head[b]						
Farm wage employment	2.030**	0.874	-0.460	0.559	0.343	0.213
Non-farm employment	-0.492	0.396	0.021	0.229	0.084	0.124
Microenterprise	0.054	0.403	-0.009	0.202	0.231*	0.132
Gender of household head (*male dummy*)	-0.543*	0.294	0.265	0.174	0.025	0.121
Household size	0.159**	0.066			-0.064***	0.022
Distance to nearest market	0.025	0.088	-0.026	0.043	0.060***	0.021
Presence of infant	-0.517**	0.220				
Type of weather forecast information received						
Extreme weather occurrence	0.955***	0.349	-0.229	0.246		
Onset of rains	-0.270	0.367	-0.222	0.229		
Occurrence of pest & diseases	-0.380*	0.208	-0.126	0.148		
Vegetation index	-1.151	2.447				
Location variables[c]						
Kaplelartet	0.832	0.760				
Kapsorok	1.485***	0.537				
NE Nyakach	0.472	0.364				
Pap Onditi	1.069*	0.604				
Soin	0.056	0.561				
Soliat	0.931	0.635				
Log household income PAE	1.429*	0.732				
Adoption of IL	**2.622*** **	**0.702**				
Farming experience			0.001	0.008		
Livestock rearing experience			-0.002	0.008		
Distance to the nearest road			0.305***	0.064	-0.139***	0.027
Lagged group membership			0.292**	0.146	-0.192*	0.102
Livestock herd in 2012 (TLU)			0.046***	0.018		
Introduction of improved livestock breeds by others in the village			0.101***	0.033		
Frequency in agrovet sourcing by others in the village			-0.009**	0.005		
Source of weather/climate information						
Radio			0.505**	0.227		
Local groups			-0.146	0.170		
Log asset index 2012					0.113***	0.042
Constant	-9.753	8.148	-2.380***	0.498	10.800***	0.720
ρ_{u_2-IL,u_1-HDDS}					-0.552***	0.138
$\rho_{\varepsilon-lnincome,u_1-HDDS}$					-0.468**	0.221
$\rho_{u_2-IL,\varepsilon-lnincome}$					-0.031	0.064
Number of observations						*424*

*; **; ***Significant at the 10%, 5%, and 1% level, respectively

[a]Base level of education is no education

[b]Reference occupation is farming (crop/livestock)

[c]Reference location is East Jimo

Table 8 Adoption and impacts of improved livestock breeds on household food sufficiency

	Hunger months		Adoption of improved livestock		Log household income PAE	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Age of household head	0.032**	0.016	0.006	0.007	-0.001	0.003
Educational status of household head[a]						
Primary	0.371	0.763	0.167	0.252	0.139	0.176
Secondary	0.188	0.918	0.106	0.280	0.256	0.207
Post-secondary	0.296	1.117	0.340	0.354	0.392	0.252
Total land owned (*acres*)	-0.059	0.077	-0.021	0.027	0.018	0.014
Main source of livelihood						
Livestock production	-0.177	0.281			-0.022	0.068
Crop production	-0.281	0.280			-0.032	0.067
Off-farm activity	-0.169	0.272			-0.012	0.065
Occupation of household head[b]						
Farm wage employment	-1.731	1.171	-0.180	0.522	0.347	0.215
Non-farm employment	-0.056	0.644	0.135	0.213	0.079	0.125
Microenterprise	-0.023	0.652	-0.017	0.206	0.226*	0.131
Gender of household head (*male dummy*)	0.534	0.540	0.333*	0.177	0.024	0.121
Household size	-0.061	0.108			-0.066***	0.022
Distance to nearest market	0.096	0.159	-0.014	0.043	0.058***	0.021
Presence of infant	-0.247	0.369				
Type of weather forecast information received						
Extreme weather occurrence	0.025	0.538	-0.179	0.244		
Onset of rains	-0.462	0.567	-0.167	0.216		
Occurrence of pest & diseases	-0.357	0.360	-0.204	0.140		
Vegetation index	3.135	3.820				
Location variables[c]						
Kaplelartet	-3.063***	1.100				
Kapsorok	-1.799**	0.890				
NE Nyakach	0.438	0.616				
Pap Onditi	-0.555	0.845				
Soin	-1.239	0.980				
Soliat	-2.759**	1.163				
Log household income PAE	-1.724	1.115				
Adoption of IL	**-4.625*****	**1.348**				
Farming experience			0.008	0.008		
Livestock rearing experience			-0.006	0.008		
Distance to the nearest road			0.286***	0.066	-0.133***	0.027
Lagged group membership			0.310**	0.150	-0.144	0.116
Livestock herd in 2012 (TLU)			0.047***	0.016		
Introduction of improved livestock breeds by others in the village			0.094***	0.032		
Frequency in agrovet sourcing by others in the village			-0.009**	0.004		
Source of weather/climate information						
Radio			0.429**	0.216		
Local groups			-0.301*	0.156		
Log asset index 2012					0.128***	0.038
Constant	24.329*	12.805	-2.407***	0.491	10.821***	0.723
$\rho_{u_2-IL,u_1-Hungermonth}$					0.599***	0.168
$\rho_{\varepsilon-lnincome,u_1-Hungermonth}$					0.508***	0.191
$\rho_{u_2-IL,\varepsilon-lnincome}$					-0.025	0.064
Number of observations						*424*

*; **; ***Significant at the 10%, 5%, and 1% level, respectively

[a]Base level of education is no education

[b]Reference occupation is farming (crop/livestock)

[c]Reference location is East Jimo

Table 9 Parameter estimates – test on the validity of the selection instruments

	Adoption of DTC	Dietary diversity score	Hunger months	Adoption of improved livestock	Dietary diversity score	Hunger months
Peer influence						
Introduction of new crop varieties by others in the village	0.065***(0.028)	0.060 (0.053)	0.053 (0.080)			
Frequency in agrovet sourcing by others in the village	-0.011 (0.007)	-0.011 (0.013)	-0.016 (0.023)	-0.009* (0.005)	-0.003 (0.010)	-0.009 (0.017)
Introduction of improved livestock breeds by others in the village				0.104*** (0.036)	0.052 (0.079)	0.054 (0.113)
Source of weather/climate information						
Radio	0.465* (0.269)	0.655 (0.372)	-0.814 (0.533)	0.326 (0.280)	0.819 (0.364)	-0.900* (0.522)
Friends and relatives	0.003 (0.192)	-0.137 (0.254)				
Local groups	0.381** (0.179)		0.627 (0.440)	-0.234 (0.192)	0.296 (0.269)	0.712 (0.449)
Wald test of peer influence & information sources	χ^2= 26.5 p = 0.000	F – stat= 1.41 p = 0.221	F – stat= 1.30 p= 0.269	χ^2= 19.9 p= 0.001	F – stat= 1.64 p= 0.164	F – stat= 1.66 p= 0.160
No. of observations	*408*	*408*	*408*	*424*	*424*	*424*

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Declarations

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