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Evaluating the impact of improved crop varieties in the Sahelian farming systems of Niger

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ABSTRACT

Most people in Niger still rely heavily on agriculture as a source of income. However, low productivity, climate change, soil infertility, pests, and diseases are challenges faced by this sector. As a result, the nation suffers from a severe problem of food insecurity. Many investigations indicate that adopting improved crop varieties(ICVs) increases agricultural productivity. Using information gathered from 1784 farmers, this study assesses the effects of adopting improved crop varieties (ICVs) on household welfare. To analyze the data, we employ endogenous switching regression (ESR) and inverse probability-weighted regression adjustment (IPWRA) techniques. The analysis shows that the ICVs adoption significantly improves household income and food access in Niger's Sahelian region. The ESR model's average treatment effects estimate shows that the ICVs adoption raised per capita income, food expenditure, and household dietary diversity score (HDDS) by 75 %, 1.81 %, and 36.49 %, respectively. The IPWRA model yields similar results.

Therefore we conclude that adopting ICVs has substantial dynamic benefits that improve household welfare in Sahel Niger by increasing their probability of escaping poverty, food insecurity, and malnutrition. The farmer's knowledge of improved crop varieties significantly influenced favorably the decision to adopt, suggesting that intensifying dissemination and encouraging the promotion of drought-tolerant crop varieties among farmers, development agencies, researchers, and policymakers could be a crucial plan of action to combat poverty, food insecurity, and malnutrition in the Sahelian region.

1. Introduction

Many countries in Sub-Saharan Africa rely heavily on agriculture as their main economic engine. Two-thirds of people in the Sahel rely on agriculture and livestock rearing [1]. Growing agricultural industry is, therefore, crucial for economic development in the Sahel region [2]. Indeed, this industry faces numerous obstacles caused by climate change, population pressure, and escalating conflicts. The repercussions. of climate change threatening the integrity of ecosystems coupled with high population growth will further exacerbate competition for natural resources, generating movement of populations and conflicts in the region [3]. Erratic rainfall followed by a short 2011–2012 cropping season in Niger, Chad, north-eastern Mali, northern Burkina Faso, and the extreme north of Nigeria caused a significant food deficit, creating a food crisis for more than 10 million people [4]. Among the Sahelian nations, the most severely impacted country by climate change and rising temperatures is Niger. Deforestation and soil erosion cause annual losses of 100,000–120,000 ha of agricultural land [5,6]. The output in agriculture has increased mainly through the expansion of cultivable land, but cultivable land is becoming scarce. Niger continues to experience high population growth, which increases pressure on limited land, resulting in the expansion of crop production on marginal land unfavorable for agriculture [7]. As well, Niger's agricultural sector faces climate change and variability challenges, including pests and diseases, some of which have become endemic. Plant pests cause estimated annual losses of around 25 % of agricultural production and post-harvest losses [5]. So, the agricultural industry needs to find strategies to boost crop productivity to cope with the increasing population demand.

A key element in encouraging success in agricultural practice is

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adopting appropriate technologies. Indeed, several institutional and economic factors, as well as household demographic attributes, influence farmers 'decision-making on technology adoption. According to Ref. [8], farm size, expected technology adoption benefits, access to credit, and extension services are the key determinants of farm households' decisions to adopt new technology in Ghana. Similarly [9],) found that adopting climate-smart agricultural technologies and practices is strongly and favorably influenced by financial availability, training, membership in an organization, household income and size, and ownership of animals of traction in the Sahelian region of Niger. Agricultural innovation can be widely disseminated and adopted with the help of extension agencies, local governments, non-governmental organizations, rural radio stations, and other local actors in West Africa [10].

Using agricultural innovations, such as drought-tolerant crop varieties, can support farmers in the Sahelian region attempting to withstand more of climate change's negative impacts. Previous findings of [11–14] demonstrated that using better climate adaptation measures boosts agricultural output, income, and food security while lowering poverty. Even though many studies have looked at the effects of better agricultural technologies, empirical evidence on the effects of adopting modern crop varieties is thin, especially in the Sahel region. By doing this study, we want to close this gap by assessing the impact of adopting improved crop varieties (ICVs) on household income and food security in the Sahelian region of rural Niger. The paper intends to add value to the existing literature on the impact evaluation of adopting agricultural technologies. The present investigation differs from previous ones regarding the technologies being taken into account (farmers adopting at least one ICV: millet, sorghum, cowpea, maize, and groundnut).

Taking into consideration selectivity bias and capturing the various adoption effects on adopters and non adopters of the technologies. We first used an endogenous switching regression on (ESR) technique. Farmers' adoption decisions are influenced by the expected benefits of the technology during the selection phase. By employing this technique, we can look at the factors that influence technology adoption and how the decision to adopt affects household welfare, particularly household income, food expenditure, and household dietary diversity score (HDDS).

To complement our findings, we also employ the inverse probability weighted regression adjustment (IPWRA) technique [15]. The IPWRA technique produces accurate estimates by simulating both the outcome andt treatment equations, but it only works when one of the two models is accurately described [16,17].

2. Methodology

This section covers the survey's design, a description of the variables, and the econometrics technique used.

2.1. Study area

The study area included Tillaberi, Dosso, Maradi, and Zinder areas of Niger, where the Climate Smart Agricultural Technologies (CSAT) project is being implemented (see Fig. 1, project intervention zones). The initiative aims to improve rural livelihoods and food and nutritional security by introducing climate-smart technologies and agricultural advances to the Sahel, Sudan, and arid Savanna regions of Niger.

Niger has a total area of 1,267,000 km^2, with the Sahara Desert occupying two-thirds of the nation. Farming and raising livestock are the main sources of income for more than 80 % of the population. Niger's gross domestic product is largely derived on agriculture, at about 40%.

2.2. Sampling, strategy, and data collection

The data for this study were gathered as part of a baseline survey for the CSAT-Niger project in Niger in 2019. All four of the regions—Dosso, Tillabery, Maradi, and Zinder—which are the project's target zones were included in the sample size.

To choose villages from each area and households from each village, a multistage sampling procedure was used. The four locations were purposefully chosen for the project in the first stage based on the level of production of cereal and legumes, agroecology, accessibility, and security. Eight communes were purposefully chosen from each of the project regions in the second stage. In the third stage, five intervention and five non-intervention villages were selected, considering accessibility, security, production of the project's main target crops (maize, sorghum, millet, cowpea, groundnut, and soybean), and the villagers' willingness to participate in the survey. (Intervention villages were those where project activities were implemented; non-intervention villages were satellite villages not benefiting from project activities.) The final stage was the random selection of households through already existing farmers' listing and communal consultation forum.

As the primary data gathering tool, a structured questionnaire was employed. Several modules were included in the questionnaire such as household demographic and socio-economic characteristics; climate change adaptation, perception and signs; food insecurity and hunger assessment scale; adoption of improved practices; and food and non-food expenditure. The information collected from 1784 households was valid and used for the analysis.

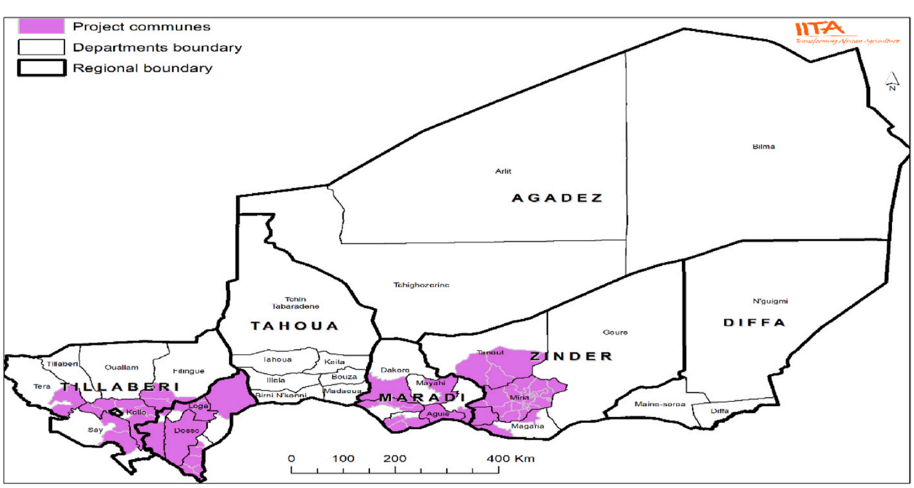

Fig. 1. CSAT-Niger Project intervention zones.
Source: Survey data (2019)

2.3. Theoritical framework and empirical strategy

Impact evaluation aims to measure the effects strictly attributable to an intervention. This is done by comparing a control group (those not participating in a program or not receiving benefits) and a target group (individuals receiving the intervention) [18,19]. The main problems faced in impact evaluation are the determination of the counterfactual and the correction of selection bias [20]. To guarantee methodological rigor, an impact evaluation must estimate the counterfactual effects: what would or could have happened if the project had never existed. To determine the comparison counterfactual, it is necessary to distinguish the effects of the interventions of other factors, a somewhat complex task.

To perfectly measure the impact of technology adoption on household welfare, exposure to the technology should be randomly assigned so that the effect of observable and unobservable characteristics between the treatment and comparison groups is the same and the effect is attributable entirely to the treatment. However, when the treatment groups are not randomly assigned, adoption decisions are likely to be influenced both by unobservable (e.g., managerial skills, motivation, land quality) and observable heterogeneity that may be correlated to the outcome of interest [21].

Heckman selection, propensity score matching, instrumental variable, and endogenous switching regression (ESR) models are often employed in adoption studies. These models, which are based on reliable hypotheses, enable the control of the selection bias issue that frequently arises in impact evaluation.

ESR is used in this work to control the issue of selection bias, following [14],22–27. Using IPWRA as a robustness check, we additionally estimate the average treatment impact of the treated (ATT).

2.3.1. Endogenous switching regression model. A Sahelian household can grow different crops on the same plot or separately in different plots. Farmers commonly mix millet, cowpea, sorghum, and groundnut on the same plot to gain higher returns.

It was assumed that a farmer's choice to utilize at least one ICV within a specific period could be categorized under the basic framework of utility and profit maximization [14],22,24,27. This is subject to land availability, credit, and other constraints [28]. A farmer will choose or adopt an ICV if the net benefits of using the technology are higher than the benefits from the local crop variety. We expect that using ICVs will help reduce the risk associated with drought and lead to an increase in yields, then to an improvement in the level of welfare of the farmer's household. The adoption of ICVs is a discrete choice resulting from maximizing a utility function. The expected utility arising from adopting ICVs, U_a, is compared to the utility of non-adoption, U_n. A farmer will adopt if $D_i^* = U_a > U_n$. D_i^* is a latent variable that captures the benefit from adopting ICVs, and is determined by a set of exogenous variables, Z_i and the error term μ_i.

$$D_i^* = Z_i\alpha + \mu_i \text{ where } D_i = \begin{cases} 1 \text{ } if \text{ } D_I^* > 0 \\ 0 \text{ } otherwise \end{cases} \tag{1}$$

If a farmer adopts ICVs, $D_i = 1$, and 0 otherwise. Z is a vector of the household, farm, and village-level variables that affect the decision to adopt and/or not adopt ICVs, and μ is an error term.

Following [14,16], the outcome functions can be expressed as an ESR model, subject to adoption:

$$\text{Regime 1 (adopters)}: y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} \text{ } if \text{ } D_i = 1 \tag{2a}$$

$$\text{Regime 2 (non}-\text{adopters}: y_{0i} = X_{0i}\beta_0 + \varepsilon_{0i} \text{ } if \text{ } D_i = 0 \tag{2b}$$

where y_{1i} and y_{0i} represent the outcome variables for adopters and non-adopters, respectively. The three error terms μ_i, ε_{1i} and ε_{0i} are assumed to have a trivariate normal distribution with a mean vector zero and covariance matrix:

$$Cov(\varepsilon_{1i}, \varepsilon_{0i}, \mu_i) = \sum = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\mu} \\ \sigma_{10} & \sigma_0^2 & \sigma_{0\mu} \\ \sigma_{1\mu} & \sigma_{0\mu} & \sigma_\mu^2 \end{bmatrix}$$

where σ_1^2 and σ_0^2 are the variances of the error terms in equations (2a) and (2b); σ_{10} is the covariance of ε_{1i} and ε_{0i}; $\sigma_{1\mu}$ represents the covariance of ε_{1i} and μ_i; and $\sigma_{0\mu}$ is the covariance of ε_{0i} and μ_i. It can be assumed that σ_μ^2 is equal to 1 since α is estimable only up to a scale factor [26]. The covariance between ε_{1i} and ε_{0i} is not defined since y_{1i} and y_{0i} are never observed simultaneously. This implies that the expected values of ε_{1i} and ε_{0i} conditional on sample selection are non-zero, because the error term in the selection equation is correlated with the error terms in equations. (2a) and (2b), and ordinary least squares estimates of coefficients β_1 and β_0 are biased.

$$E(\epsilon_1 | D_i = 1) = \sigma_{\epsilon 1\varepsilon}\frac{\varphi(Z_i\beta_i)}{\Phi(Z_i\beta_i)} = \sigma_{\epsilon 1\varepsilon}\lambda_1 \tag{3a}$$

$$E(\epsilon_0 | D_i = 0) = \sigma_{\epsilon 0\varepsilon}\frac{-\varphi(Z_i\beta_i)}{1-\Phi(Z_i\beta_i)} = \sigma_{\epsilon 0\varepsilon}\lambda_0 \tag{3b}$$

where φ and Φ are the probability density and the cumulative distribution function of the standard normal distribution, respectively.

If $\sigma_{\epsilon 1\varepsilon}$ and $\sigma_{\epsilon 0\varepsilon}$ are statistically significant, this would indicate that the decision to adopt is correlated with the outcome variable of interest, suggesting evidence of sample selection bias.

$$\frac{\varphi(Z_i\beta_i)}{\Phi(Z_i\beta_i)} = \lambda_1 i \text{ and } \frac{\varphi(Z_i\beta_i)}{1-\Phi(Z_i\beta_i)} = \lambda_{2i}$$

where λ_1 and λ_2 are the inverse mills ratio calculated from the selection equation, and will be included in equations (3a)–(3b) to correct for selection bias in a two-step estimation procedure.

The above-mentioned ESR model is estimated using the effective full information maximum likelihood (FIML) estimation approach.

The FIML also generates correlation coefficients, i.e., correlations of the error terms of the selection and outcome equations (corr ($\boldsymbol{\varepsilon}$, μ) = ρ). There is endogenous switching if ρ_A or ρ_N (which are correlation coefficients for adopters and non-adopters, respectively) are significantly different from zero [27,29]. The signs of the correlation terms have an important economic interpretation [27,29,30]. If $\rho_A < 0$, it implies positive selection bias, which suggests that farmers with above-average income and assets are more likely to adopt ICVs. On the other hand, if $\rho_N > 0$, it implies negative selection bias. Though, the model may be identified by construction through nonlinearities generated in the selection equation; the Z variables in the selection model need to contain an instrument for a more robust identification. We use awareness of improved seed varieties and climate change signs index as selection instruments. We hypothesize that when the farmers are exposed to and aware of ICVs, it will increase their adoption and they will gain more benefits from it. An index was constructed using principal component analysis from the farmers' responses on how they experienced changes in climate signs, such as rain patterns, amount of rain, frequency of droughts, flooding, temperature, cold, and heat.

The above ESR framework can be used to estimate the average treatment effect of the treated (ATT), and of the untreated (ATU), by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios.

Following [8,31], we calculate the ATT and ATU as follows.

For an adopter of ICVs, the expected value of the outcome variable is expressed as:

$$E(y_{1i} \backslash D_i = 1, X) = X_{1i}\beta_1 + \sigma_{\epsilon 1\varepsilon}\lambda_{1i} \tag{4}$$

The expected values for the same farmer had they decided not to adopt ICVs (counterfactual) are given as:

$$E(y_{0i} \backslash D_i = 1, X) = X_{1i}\beta_0 + \sigma_{\epsilon 0\epsilon}\lambda_{1i} \quad (5)$$

The impact of adoption on the outcome variables for those who adopted ICVs—i.e., the average ATT—is calculated as the difference between equations (4) and (5).

$$ATT = E(y_{1i} \backslash D_i = 1;\ X) - E(y_{0i} \backslash D_i = 1;\ X) \quad (6)$$

$$= X_{1i}(\beta_{1-}\beta_0) + (\sigma_{\epsilon 1\epsilon} - \sigma_{\epsilon 0\epsilon})\lambda_{1i}$$

2.3.2. Inverse probability weighted regression adjustment. The issue with equation (6) is that it is not possible to observe the outcome of ICVs adopters had they not adopted, i.e., $E(y_{0i}/D_i = 1;\ X)$. However, by substituting the results of non-adopters for these unobserved counterfactuals $E(y_{0i}/D_i = 0;\ X)$ may result in biased ATT estimates [32,33]. We used the doubly robust inverse probability weighted regression adjustment (IPWRA) model to resolve this issue [15]. The IPWRA technique relies on two presumptions to estimate treatment effects. The first presumption is known as the conditional independence assumption, sometimes known as unconfoundedness, and it states that once we condition on a large number of covariates, the treatment assignment is effectively random. This is a strong and contentious premise that self-selection into treatment may still be dependent on imperceptible factors [15]. However, by conditioning on a wide range of covariates that we have in our data set in equation (2), we attempt to lessen the selection of unobservables. The second hypothesis, also referred to as the overlap hypothesis, states that everyone has a positive probability of obtaining treatment when conditional on a set of covariates.

If this assumption is true, it ensures that for every adopting household in the sample, we observe some non-adopting households with similar covariates. This IPWRA model permits the estimation of both the outcome and treatment equations, but only one of the two models needs to be accurately described in order to estimate the impact consistently. Regression adjustment (outcome model) and inverse probability weighting (treatment model) are used to provide the estimator of IPWRA.

Formally, the ATT for the IPWRA estimator can be written as:

$$ATT_{\text{IPWRA}} = n_A^{-1} \sum_{i=1}^{n} T_i \left[r_A^*(X, \delta_A^*) - r_N^*(X, \delta_A^*) \right] \quad (7)$$

where nA is the number of adopters and ri (X) is the postulated regression model for the adopters (A) and non-adopters (N) based on observed covariates X and parameters $\delta_i = (\alpha_i, \beta_i)$. The * on the estimated parameters r, β, and X describes the double robustness result.

$\delta_A^* = (\alpha_A^*,\ \beta_A^*)$ is acquired by the weighted regression method

$$\min_{\alpha_A^*, \beta_A^*} \sum_{I=1}^{N} T_i \left(y_i - \alpha_A^* - X\beta_A^*\right)^2 \Big/ \dot{\rho}(X, \dot{\gamma}) \quad (8)$$

and $\delta_N^* = (\alpha_N^*,\ \beta_N^*)$ is obtained using the weighted regression technique:

$$\min_{\alpha_N^*, \beta_N^*} \sum_{I=1}^{N} (1 - T_i)\left(y_i - \alpha_N^* - X\beta_N^*\right)^2 \Big/ (1 - \dot{\rho}(X, \dot{\gamma})) \quad (9)$$

where $\dot{\rho}(X, \dot{\gamma})$ are the estimated propensity scores, and X is a vector of covariates based on observed characteristics.

2.3.3. Variable definition and descriptive statistics. In Table 1, we provide the definitions and descriptive statistics for the selected variables. The welfare indicators include household per -capita income, per-capita household food expenditure [27], and household dietary diversity score (HDDS) as an indicator of dietary diversity(access to food) [30]. The HDDS, ranging from 1 to 12, measures the proportion of the 12 food groups that include all food ingested by any household member during the reference period.

The treatment variable is the adoption of at least one drought-resistant crop variety (millet, sorghum, cowpea, groundnut, maize). In the Sahelian region, farmers usually mix millet, cowpea, sorghum, and groundnut on the same plot to gain higher returns, according to cropping systems provided by researchers. This also helps to minimize risks

Table 1
Summary statistics of rural households by adoption status.

Variable	Description	Full sample (N = 1783)	SD	Adopters (N = 1122)	Non-adopters (N = 661)	Difference
Outcome variables						
Total household income	Total household income per capita	30,108.20	9155.21	344,167.50	230,715.50	113,452
Total household food expenditure	Total household expenditure per capita	2,333,818	181,838.70	2,556,491	1,955,848	600,642.90
HDDS	Household dietary diversity score (number)	5.61	0.04	5.75	5.36	0.38
Treatment variables						
Adoption of Improvedcrop varieties (ICVs)	1 = if adopt at least one ICV (millet, sorghum, cowpea, groundnut, maize); 0 otherwise	0.62	0.48			
Explanatory variables						
Gender	Dummy = 1 if household head is male	0.82	0.00	0.87	0.73	0.13
Age	Age of household head	49.20	0.32	49.42	48.82	0.59
Household size	Total size of household	10.99	0.14	11.21	10.63	0.57
Farm size	Total size of landholding (ha)	5.06	0.13	5.37	4.54	0.82
Education	Number of years' education	2.19	0.11	2.19	2.18	0.01
Farming experience	Number of years' farming	27.01	0.34	27.70	25.83	1.87
Possession of irrigated land	Dummy = 1 if owned irrigated land	0.15	0.00	0.16	0.13	0.03
Tropical livestock units (TLU)	Livestock ownership in TLU	6.20	0.19	7.07	4.73	2.33
Access to credit	Dummy = 1 if household has access to credit	0.33	0.01	0.34	0.31	0.03
Membership	Dummy = 1 if household head is member of an organization or association	0.26	0.01	0.27	0.22	0.05
Contact with extension agent	Dummy = 1 if household has contact with public extension services	0.39	0.01	0.46	0.28	0.17
Training	Dummy = 1 if one (at least) household member attended training	0.15	0.00	0.19	0.08	0.10
Climate information	Dummy = 1 if household obtained information on rainfall and temperature	0.62	0.01	0.62	0.63	0.00
Access to markets	Distance to nearest main road (km)	5.75	0.17	6.21	4.97	1.23
Instrumental variables						
Awareness of improved seed varieties	Dummy = 1 if household aware of improved seed varieties	0.26	0.01	0.33	0.13	0.19
Climate change signs index	Climate change index (number)	6.91	0.04	−0.02	0.04	0.07

related to climate.

The explanatory variables include age, household size, gender, farming experience, education, membership, farm size, ownership of irrigated land, number of animals, access to credit, training, contact with extension, access to markets, whether they obtained climate information and awareness of improved seed varieties. These factors are thought to have an impact on farmers' productivity, income, and food security status, as well as their decisions regarding adoption.

The mean differences between adopters and non-adopters' attributes are also presented.

3. Results and discussion

3.1. Adoption of improved crop varieties

Several development projects disseminate agricultural technologies and practices across Niger. These technologies were introduced to farmers by agricultural extension services, which use approaches such as farmer demonstration fields, contact groups, training and visits, farmer open days, and specialized advice. The new agricultural technologies introduced by research institutions aim to increase agricultural productivity and income of rural dwellers, thereby mitigating negative impacts of climate change on household incomes and food security.

The descriptive results presented in Table 2 show low rates of adoption of improved crop varieties by farmers. The adoption rate is higher in cowpea (more than 50 %), followed by millet (36.77 %), while less than 4 % adopted improved maize varieties. There could be several reasons for non-adoption, which include lack of access to these technologies, and high costs seeds.

3.2. Determinants of ICVs adoption

Table 3 presents the main determinants of the adoption of ICVs (selection equation) and income per capita (outcome equations). In Appendix A, the factors that affect food expenditure and HDDS are listed (Tables A2 and A3). The selection equation's results demonstrate that household' socioeconomic and demographic characteristics are substantially related to the adoption of ICVs.

The decision to use ICVs is positively impacted by the household head's gender, which is statistically significant. This finding suggests that male farmers are more inclined than female farmers to accept new agricultural technologies. The reason for this is because in the Sahel region, the lands are owned by males who are more exposed to new agricultural technologies. The customary law limits women's land ownership [34]. In addition, Women in the Sahel are highly excluded from political life [35]. This is consistent with the findings of [27]. Because experienced farmers are more likely to be aware about methods for boosting agricultural production, hence the positive association with adopting ICVs. As expected, training and extension services positively and significantly affect the adoption of ICVs.

This indicates that farmers are more likely to embrace ICVs to boost agricultural productivity if they have access to extension services and training. Livestock ownership also has a significant and positive effect on farmers' decision to adopt ICVs. Animals such as cattle, donkeys, and horses are used for transportation and as animal traction for farm operations. Housheold can sell and purchase new agricultural technology to boost farm production. The results of [36–38] support this conclusion.

Table 2
Adoption of improved crop varieties.

Improved crop varieties	Adoption rate (%) $N = 1784$
Maize	03.13
Millet	36.77
Sorghum	17.20
Cowpea	50.33
Groundnut	11.26
Overall	23.73

Table 3
Full information maximum likelihood of endogenous switching regression—income.

Independent variables	Income per capita (log)		
	Selection	Adopters	Non-adopters
Sex (yes = male)	0.563(0.08)***	1.32(0.31)***	2.23(0.38)***
Age of household head (years)	−0.001 (0.00)	−0.01(0.00)	−0.01 (0.01)
Household size (number)	0.011(0.00)**	−0.02(0.01)	−0.11 (0.02)***
Farm size (number)	−0.001 (0.00)	−0.02(0.01)	0.01(0.02)
Education (yes = 1)	−0.005 (0.00)	0.004(0.01)	−0.008 (0.02)
Farming experience (years)	0.009 (0.003***	−0.01(0.00)*	0.03(0.01)**
Owned irrigated farmland (yes = 1)	0.006(0.08)	0.75(0.17)***	0.32(0.36)
Tropical livestock units (TLU)	0.022(0.00)***	0.03(0.00)***	0.13(0.02)***
Access to credit (yes = 1)	0.018(0.06)	0.78(0.14)***	0.60(0.31)*
Membership (yes = 1)	0.061(0.07)	0.07(0.16)	−0.09 (0.34)
Contact with extension agent (yes = 1)	0.394(0.06)***	0.73(0.15)***	1.76(0.29)***
Attended training (yes = 1)	0.410(0.09)***	0.34(0.17)*	2.12(0.43)***
Access to climate information (yes = 1)	−0.041 (0.06)	0. 17(0.17)	−0.30 (0.27)
Occurrence of drought	0.086(0.06)	−0.65(0.17)***	0.29(0.28)
Distance to nearest market (km)	0.009(0.00)**	0.04(0.00)***	0.06(0.02)***
Awareness of improved seed varieties	0.219(0.02)***		
Climate change signs index	0.002(0.00)		
Constant	−0.622 (0.16)***	7.90(0.48)***	10.00(0.74)***
Number of observations	1783	1122	661
Log–likelihood	−5181.35		
Wald $chi^2(15)$	198.45		
Prob > chi^2	0.0000		
rho_1		0.99*** (0.00)	
rho_0			0.08*** (0.03)
Wald test of independent equations $chi^2(2) = 739.93$	Prob > chi^2 =	0.0000	

Note: Figures in parentheses are standard errors. ***, **, *, significant at 1 %, 5 %, 10 %, respectively.

The positive coefficient for distance to the nearest market shows that the probability of using ICVs increases with closeness to the main market. This implies that the availability of transportation infrastructure facilitates farmers' access to improved agricultural technologies in general. Similarly, awareness of improved seed varieties has a positive and significant effect on adopting ICVs.

However, the likelihood of adoption is considerably and negatively correlated with household size. This suggests that smaller households are more likely to embrace ICVs than bigger ones. This is in line with the conclusions of [39,40], who reported that household size has a negative and statistically significant effect on the adoption of improved soybean varieties.

Table 3 displays the results for the income outcome equations. The findings demonstrate that gender has a favorable and significant impact on both adopters and non-adopters' incomes. This shows that, as compared to households headed by women, households headed by men are more likely to have greater wages. This is not surprising because most agricultural land is in the hands of males. This is consistent with the conclusions reached by Refs. [39–42]. The incomes of both adopters and non-adopters are positively and significantly impacted by owning animals, in a similar manner. This can be explained by the fact that in West Africa, raising livestock is one of the key economic activities on which the poorest inhabitants rely for both food and revenue [40,43]. Other significant factors affecting the incomes of both ICV adopters and non-adopters include access to credit, extension services, training, and distance to the major market.

3.3. Impact of adoption of ICVs on household welfare

3.3.1. Results of the endogenous switching regression model

Table 4 presents estimates of the ATT, which show the impact of ICVs adoption on household welfare indicators using the ESR model. This indicate that adoption of ICVs is linked with an increase in selected household welfare indicators. Results suggest that the per capita income increased by 75 % due to the adoption of ICVs.

Adopting ICVs is also associated with a significant increase of 1.81 % in household per capita food expenditure. Likewise, compared to counterfactuals, adopters' HDDS increased by 36 % as a result of using ICVs. These results are in line with many studies conducted in West Africa [12,24,27,44], which reveal that the adoption of agricultural technologies increases household per capita food expenditure. In Niger [42], found that farmers who used improved varieties of millet and cowpea could consume their products for 5 months, while the produce of their counterparts lasted only 3 months.

3.3.2. Results of the inverse probability weighted regression model

We also estimated the ATT using the IPWRA model. Table 5 provides the results. According to these results, adoption increases household per capita income, food expenditure, and HDDS by 0.55 %, 5.34 %, and 3.54 % respectively. These results confirm the above results of the ESR model regarding the positive impact of adoption on household income and food security. These results are supported by the findings of previous studies conducted by Refs. [43,45,46] in Africa.

4. Conclusion

Current issues having a marked impact on the development of Sahelian countries include droughts, floods, crop pests, rising prices of food products and agricultural inputs, and inter-community tensions over access to scarce resources. Beyond these factors, the unstable political environment and armed conflicts seriously affect the livelihoods of Sahelian people.

The adoption of quality seeds is an important element of increasing agricultural productivity. For most countries in sub-Saharan Africa, agriculture remains the primary source of revenue for most of the population, and raising of agricultural production is a key goal for national and household food security. Suitable quality seeds are necessary to meet the requirements of various agroclimatic conditions and intensive cropping systems. In this study, we used data collected from 1784 rural households in Niger's four major agricultural zones to evaluate the impacts of the adoption of improved crop varieties on household income and food security.

All of the estimating techniques used in this investigation produce fairly similar empirical results. They indicate that adopting ICVs has a significant positive impact on household income and food security in rural Niger. The average treatment effects estimate from the ESR model indicate that per capita income, per capita food expenditure, and HDDS increase by 75 %, 1.81 %, and 36.49 %, respectively, with the adoption of ICVs. The IPWRA results are similar, although they differ from ESR in the magnitude of effects.

These results demonstrate that the adoption of ICVs has substantial benefits that improve household welfare in Sahel Niger.

Currently, food security and the resilience capacity of populations are two major concerns of the Niger Government, and are therefore at the center of priorities. By consistently increasing productivity and producing the key food crops for the social welfare of Nigerien citizens, the government hopes to secure food security. This challenge cannot be overcome without resorting to the use of improved seeds, which will require their availability in quantity and quality to meet farmers' needs. In addition, the significance of farmers' contacts with extension agents and awareness of ICVs to their adoption of improved varieties suggests that intensifying the dissemination and promotion of ICVs among farmers could be a key strategy to reduce poverty, food insecurity, and malnutrition in the Sahelian region.

Table 4
Impact of adoption of ICVs on income and expenditure.

Outcome	Adopters	Non-adopters	ATT	Change in outcome (%)
Income per capita (log)	15.97 (0.04)***	9.12(0.03) ***	6.84 (0.02) ***	75.05
Annual per capita food expenditure (log)	11.56 (0.00)***	11.35 (0.01)***	0.20 (0.00) ***	1.81
Household dietary diversity score (HDDS)	7.85(0.02) ***	5.75(0.01) ***	2.10 (0.02) ***	36.49

Note: Figures in parentheses are standard errors. ***, **, *, significant at 1 %, 5 %, 10 %, respectively.

Table 5
Impact of adoption of ICVs using IPWRA.

Outcome	Adopters	Non-adopters	ATT	% Change in outcome
Income per capita (log)	9.12***	8.81***	0.31 (0.16)*	3.54 %
Annual per capita food expenditure (log)	11.32	11.26***	0.06 (0.06)	0.55 %
Household dietary diversity score (HDDS)	5.75***	5.46***	0.29 (0.12)**	5.34 %

Note: Figures in parentheses are standard errors. ***, **, *, significant at 1 %, 5 %, 10 %, respectively.

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CRediT authorship contribution statement

Zakari Seydou: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Investigation. **Manda Julius:** Methodology, Writing – review & editing, Data curation, Validation. **Ibro Germaine:** Conceptualization, Data curation, Supervision, Writing – review & editing. **Bokar Moussa:** Conceptualization, Data curation, Supervision, Writing – review & editing. **Tahirou Abdoulaye:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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Appendix A

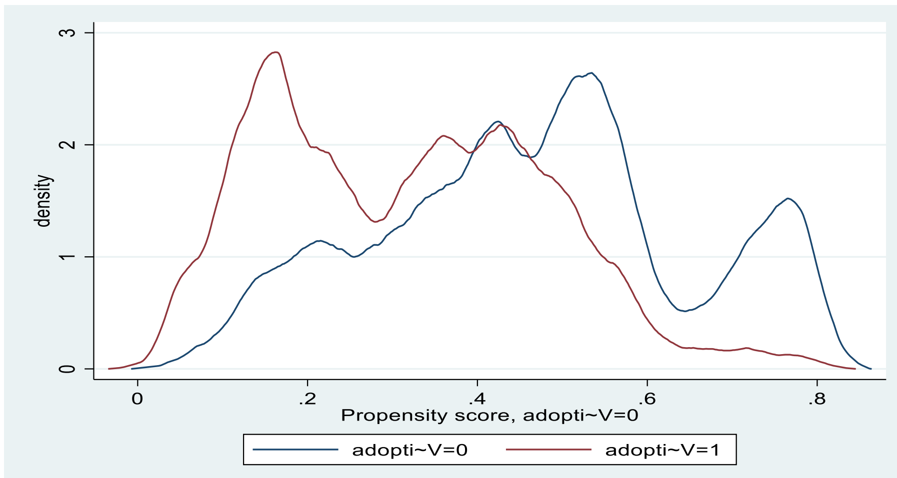

Fig. A1. IPWRA overlap plots.

Table A1
Covariate balance summary

		Raw		Weighted
Number of observations	=	1783		1783.0
Treated observations	=	1122		874.8
Control observations	=	661		908.2
	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
Awareness of improved seed varieties	0.4736361	−0.0743722	1.870699	0.9546289
Climate hange signs index	−0.0361134	−0.0441899	0.9804771	0.9141218
Gender (yes = male)	0.3592502	−0.0639878	0.5530004	1.172176
Age of household head (years)	0.0429911	0.063799	1.02476	1.033527
Household size (number)	0.0897679	0.0130583	0.799987	0.8885794
Farm size (number)	0.1457209	0.0383776	1.951434	1.598035
Education (yes = 1)	0.0037921	−0.0022238	0.6884678	0.7712498
Farming experience (years)	0.1272888	0.0370001	0.9085135	0.9171902
Owned irrigated farmland (yes = 1)	0.0895564	0.0103772	1.191281	1.018989
Tropical livestock units (TLU)	0.2936992	0.0694913	2.204732	1.3085
Access to credit (yes = 1)	0.0802192	0.0720612	1.058954	1.052734
Membership of organization (yes = 1)	0.1182297	−0.0043307	1.142723	0.9958243
Contact with extension agent (yes = 1)	0.3760765	−0.0464006	1.224316	0.9950804
Attended training (yes = 1)	0.3058904	−0.0384461	1.957649	0.9434897
Access to climate information (yes = 1)	−0.0144206	0.0013776	1.007005	0.9993393
Occurrence of drought	0.0697922	−0.0476546	0.9372046	1.052195
Distance to nearest market (km)	0.1722616	−0.0183716	1.691407	1.149674

Table A2
Full information maximum likelihood of endogenous switching regression – Food expenditure

Independent variables	Per capita food expenditure (ln)		
	Selection	Adopters	Non-adopters
Gender (yes = male)	0.60(0.09)***	0.49(0.12)***	0.22(0.12)*
Age of household head (years)	0.00(0.00)	−0.00(0.00)	−0.00(0.00)
Household size (number)	−0.00(0.00)	−0.04(0.00)***	−0.03(0.00)***
Farm size (number)	0.00(0.00)	0.01(0.00)***	0.01(0.00)
Education (yes = 1)	−0.00(0.00)	0.01(0.00)	0.01(0.00)**
Farming experience (years)	0.00(0.00)	0.01(0.00)***	0.01(0.00)**
Owned irrigated farmland (yes = 1)	−0.02(0.08)	0.06(0.09)	0.11(0.13)
Tropical livestock units (TLU)	0.01(0.00)***	0.01(0.00)***	0.00(0.00)
Access to credit (yes = 1)	0.00(0.07)	−0.22(0.08)***	0.08(0.09)
Membership of organization (yes = 1)	0.12(0.07)	0.11(0.09)	0.14(0.11)
Contact with extension agent (yes = 1)	0.27(0.06)***	0.05(0.08)	−0.09(0.11)
Attended training (yes = 1)	0.39(0.09)***	0.21(0.09)**	−0.04(0.15)
Access to climate information (yes = 1)	0.06(0.06)	0.40(0.08)***	0.34(0.09)***
Occurrence of drought	0.08(0.06)	0.24(0.07)***	0.23(0.08)***
Distance to nearest market (km)	0.00(0.00)**	0.01(0.00)***	0.00(0.00
Awareness of improved seed varieties	0.58(0.08)***		
Climate change signs index	0.00(0.01)		
Constant	−0.87(0.16)***	9.90(0.21)***	11.08(0.21)***
Number of observations	1783	1122	661
Log likelihood	−3611.67		
Wald $chi^2(15)$	76.61		
Prob > chi^2	0.0000		
rho_1		0.89***(0.2)	
rho_0			0.14***(0.10)
Wald test of independent equations $chi^2(2) = 174.99$	Prob > chi^2	= 0.0000	

Note: Figures in parentheses are standard errors. ***, **, *, significant at 1 %, 5 %, 10 %, respectively.

Table A3
Full information maximum likelihood of endogenous switching regression – HDDS

Independent variables	HDDS		
	Selection	Adopters	Non-adopters
Gender (yes = male)	0.63(0.09)***	0.07(0.20)	0.62(0.26)**
Age of household head (years)	0.00(0.00)	−0.01(0.00) *	−0.00(0.00)
Household size (number)	−0.01(0.00)**	0.00(0.01)	−0.00(0.01)
Farm size (number)	0.00(0.00)	−0.00(0.01)	−0.01(0.01)
Education (yes = 1)	−0.00(0.00)	0.00(0.00)	0.00(0.01)
Farming experience (years)	0.00(0.00)	0.00(0.00)	0.01(0.00) *
Owned irrigated farmland (yes = 1)	−0.01(0.09)	0.63(0.16)***	0.33(0.23)
Tropical livestock units (TLU)	0.02(0.00)***	0.01(0.00)**	0.05(0.02)***
Access to credit (yes = 1)	−0.03(0.07)	−0.01(0.13)	0.36(0.18)*
Membership of organization (yes = 1)	0.13(0.07)*	0.00(0.14)	0.05(0.21)
Contact with extension agent (yes = 1)	0.30(0.06)***	−0.06(0.13)	0.97(0.19)***
Attended training (yes = 1)	0.50(0.01)***	0.24(0.17)	0.76(0.34)**
Access to climate information (yes = 1)	0.05(0.06)	0.16(0.13)	0.10(0.17)
Occurrence of drought	−0.00(0.07)	−1.14(0.13)***	−0.31(0.18) *
Distance to nearest market (km)	0.00(0.00)*	0.02(0.00)***	0.040(0.01) ***
Awareness of improved seed varieties	0.86(0.08)***		
Climate change signs index	−0.01(0.01)		
Constant	−0.91(0.17)***	6.35(0.40)***	5.39(0.45)***
Number of observations	1783	1122	661
Log likelihood	−4782.1467		
Wald $chi^2(15)$	= 75.78		
Prob > chi^2	0.0000		
rho_1		0.24***(0.09)	
rho_0			0.60***(0.11)
Wald test of independent equations $chi^2(2) = 20.17$	Prob > chi^2 =	0.0000	

Note: Figures in parentheses are standard errors. ***, **, *, significant at 1 %, 5 %, 10 %, respectively.

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