ORIGINAL ARTICLE OPEN ACCESS

Improving the Productivity and Income of Smallholder Sorghum Farmers: The Role of Improved Crop Varieties in Nigeria

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ABSTRACT

Among others, biotic and abiotic constraints associated with climate variability contribute to the low productivity of sorghum in Nigeria and other Sub-Saharan African countries. In this regard, improved sorghum varieties (ISVs) have been developed to address the constraints and boost the productivity of smallholder sorghum farmers. However, there is a scarcity of empirical studies on the adoption and impacts of ISVs. Using plot-level data from 3308 plots, we examine the drivers and impacts of the adoption of ISVs on the productivity and net income of sorghum farmers in Nigeria. To do so, we estimate an endogenous switching regression (ESR) model, which accounts for potential selection bias from observed and unobserved heterogeneity, and we perform some robustness checks. Our results show that the adoption rate of ISVs is about 25% in the study area. Among other factors, access to varietal information and distance to the seed market strongly explain the adoption of ISVs. The adoption of ISVs led to an increase in sorghum yield and net income by 13% and 17% respectively. Our results suggest that most smallholder sorghum farmers will not benefit from the productivity and income gains, given the relatively low adoption of ISVs. Overall, our findings imply that policymakers and development partners should increase investments in promoting the widespread adoption of ISVs through interventions, such as improved extension services and accessibility of seeds to deliver productivity gains to smallholder sorghum farmers.

1 | Introduction

Sorghum [*Sorghum bicolor* (L.) Moench] is an important cereal crop cultivated by farmers in semiarid and arid regions of tropical Asia and Africa (Mrema et al. 2020; Kante et al. 2019; Ajeigbe et al. 2018). It is a major dietary staple among 300 million people across over 30 countries and an important raw material for many agro-allied industries, which expands the crop's potential to become a valuable source of income for smallholder farmers (Coulibaly et al. 2020; Winchell et al. 2018). Furthermore, in arid environments, it is more resilient to adverse biophysical conditions, such as drought and high temperatures compared to other cereals, such as maize (Abdelhalim et al. 2021; Muller et al. 2020; Hariprasanna and Rakshit 2016). However, despite the potential of sorghum, the yield of the crop is often less than 1 ton per hectare, on average, which is below the yield potential ranging from 2.5 to 3.5 tons per hectare in Nigeria (Ahmad Yahaya et al. 2022; Ajeigbe et al. 2019).

Enhancing agricultural productivity remains a vital pathway for addressing rural poverty and food insecurity, aligning closely with the United Nations' first and second Sustainable Development Goals (Gollin et al. 2021; Ligon and Sadoulet 2018). However, the persistently low yields of sorghum and other crops in Sub-Saharan Africa (SSA) present a substantial challenge to realising these objectives (Wollburg et al. 2024). Proof of this is a recent study by Vicente-Serrano et al. (2024) who estimate that climate-induced reductions in agricultural productivity could jeopardise livelihoods to such an extent that they might erode 12% of the continent's total GDP.

The low yield of sorghum is not peculiar to farmers in Nigeria alone, as studies from other parts of SSA have also reported a similar situation (Musara and Musemwa 2020; Smale et al. 2018; Traore et al. 2017). Factors attributed to this low yield are biotic and abiotic stresses, which include erratic rainfalls, drought, poor soil fertility, pests and diseases, exacerbated by climate variability and poor agronomic management practices, among others (Sebnie et al. 2020; Ajeigbe et al. 2019; Mengistu et al. 2019; Mrema et al. 2020). Notably, Abraha et al. (2015) reported that drought stress in sorghum during anthesis can result in yield loss of up to 70%. This potential devastation by drought to sorghum yield is extremely damaging to the livelihoods of smallholder farmers who mostly rely on it for their food security needs and as a primary source of income.

In this regard, the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) with National Agricultural Research Systems (NARs) and other partners have developed high-yielding, multi-stress tolerant and early-maturing varieties of sorghum to address the biotic and abiotic stresses (Ajeigbe et al. 2019; Ndjeunga et al. 2015). Several donor-funded projects and government-led interventions have helped disseminate these ISVs to farmers across northern Nigeria. While the development and dissemination efforts for sorghum are notable, empirical evidence on the impact of the adoption of ISVs on the productivity and welfare of sorghum farming households in Nigeria is scarce.

Existing empirical evidence on the impact of the adoption of improved crop varieties on the productivity and welfare of smallholder farmers from different parts of SSA has mainly focused on crops such as maize (Martey et al. 2020; Oyinbo et al. 2019; Abdoulaye et al. 2018; Khonje et al. 2015), rice (Bello et al. 2021; Arouna et al. 2017; Wiredu et al. 2014), cowpea (Manda et al. 2020, 2019; Alene and Manyong 2006), cassava (Wossen et al. 2019; Awotide et al. 2015), groundnut (Jelliffe et al. 2018; Kassie et al. 2011; Moyo et al. 2007) and soybean (Kamara et al. 2022). These studies reported mixed results on the productivity and welfare effects of adopting improved crop varieties in different parts of SSA. Despite the considerable varietal improvement research for sorghum in SSA, empirical studies on the determinants and impacts of adopting ISVs are sparse. To our knowledge, only Musara and Musemwa (2020) and Smale et al. (2018) provided evidence of the impact of the adoption of ISVs in Zimbabwe and Mali respectively. To this end, it remains unclear whether and to what extent the adoption of ISVs delivers productivity and welfare gains to sorghum-growing households in Nigeria.

In this paper, we analyse the factors that influence the adoption of ISVs and the impact of the adoption of ISVs on the productivity and net income of smallholder sorghum-growing households in Nigeria. We make two contributions to the literature. We document the impacts of improved varieties of sorghum, a critical food security crop that has been largely overlooked in the agricultural technology adoption and impact evaluation literature. In this way, we build on the very few studies that have tried to document the impacts of sorghum technologies in SSA (Musara and Musemwa 2020; Smale et al. 2018). Second, our paper relies on nationally representative household survey data from a sample of 1677 sorghum-growing households in the sorghum belt of Nigeria. Using nationally representative data strengthens our findings' external validity for Nigeria's sorghum belt. In this way, we build on the previous studies on adoption and impacts of sorghum technologies in SSA and other studies on technology adoption and impacts that do not leverage the use of nationally representative data (e.g., Amadu et al. 2020; Bello et al. 2021; Oyinbo et al. 2019; Khonje et al. 2015), From a methodological perspective, we employed the endogenous switching regression (ESR) model for our estimation to control for potential selection bias arising from observable and unobservable heterogeneity, and we perform robustness checks using the propensity score matching (PSM) and the inverse weighted probability regression adjustment (IPWRA) to strengthen the internal validity of our findings. This builds on the estimation approaches of previous empirical studies on the impacts of varietal adoption that do not account for possible selection bias from unobserved heterogeneity (e.g., Oyinbo et al. 2019; Smale et al. 2018; Kassie et al. 2011; Mendola 2007).

2 | Sorghum Interventions in Northern Nigeria

International Crop Research Institute for the Semi-Arid Tropic and its partners, both national and international, have been developing and disseminating ISVs and best agronomic management practices for sorghum-growing countries in West and Central Africa for some time now (Weltzien et al. 2018; Ndjeunga et al. 2015). In Nigeria, for instance, this partnership has resulted in the development of ISVs with varying agronomic traits suitable for the diverse agro-ecological zones in the sorghum belt of Nigeria over the years. The varieties are high-yielding, with grain yield potentials ranging from 2.5 to 3.5 t/ha. The most recent varieties that have been released in Nigeria are Samsorg 45, Samsorg 46, Samsorg 47, Samsorg 48, CSR-01, CSR-02, CSR-03 H and CSR-04 H, among others. Other traits of the ISVs include extra-early, early and medium maturity, high content of Fe and Zn, high stover, tolerance to the parasitic weed *Striga hermonthica*, good malting qualities and staying green characteristics that confer tolerance to drought (Ajeigbe et al. 2019).

Several donor-funded projects in Nigeria have directly and indirectly contributed to promoting these ISVs and associated agronomic management practices through field days, demonstration trials, seed multiplication, extension services, capacity building of stakeholders and strategic partnerships with seed companies and community-based organisations. These include the Harnessing Opportunities for Productivity Enhancement of sorghum and pearl millet (HOPE 1 and HOPE 2) projects (2009–2020) and the West Africa Agricultural Productivity Project

(WAAPP) (2013–2015), among others. The former also contributed to developing some varieties, such as Samsorg 45, Samsorg 46, Samsorg 47, Samsorg 48 and Samsorg 49. Other projects include the Technologies for African Agricultural Transformation (TAAT) project and the Accelerated Varietal Improvement and Seed Delivery of Legumes and Cereals in Africa (AVISA) project. Through the Agricultural Transformation Agenda (ATA) (2012–2015), the Federal Government of Nigeria promoted the use of ISVs to improve sorghum productivity and develop the sorghum value chain. Building on the ATA programme, the Agricultural Transformation Agenda Support Program-Phase 1 (ATASP-1) (2015–2021) is promoting the use of ISVs and youth and women capacity building to improve the development of the sorghum value chain.

3 | Study Area and Data

We conducted the study in northern Nigeria, where the bulk of sorghum production in the country takes place. According to Ajeigbe et al. (2019), although sorghum can be produced virtually in all States in Nigeria, Adamawa, Bauchi, Benue, Borno, Gombe, Jigawa, Kaduna, Kano, Katsina, Kebbi, Kogi, Kwara, Nasarawa, Plateau, Sokoto, Taraba and Zamfara States remain the leading producers in the country, and these states are often dubbed 'the sorghum belt of Nigeria'. To ensure that the states and respondents for this study are good representatives of the sorghum belt in Nigeria, we purposefully selected nine states (Jigawa, Sokoto, Kano, Kebbi, Katsina, Niger, Adamawa, Bauchi and Gombe) in northern Nigeria based on the quantity of sorghum production. The selected states are not only the largest producers of sorghum in Nigeria but also spread across different agro-ecological zones, covering southern Guinea Savanna, northern Guinea Savanna, Sudan Savanna and Sahel savanna agro-ecological zones of Nigeria.

In this study, we employed a three-stage sampling technique to select sorghum-growing households. In the first stage, we applied a probability proportional to size sampling to select four local government areas (LGAs) each in five states (Kano, Katsina, Niger, Bauchi and Adamawa) and two LGAs each in four states (Sokoto, Kebbi, Jigawa and Gombe) giving a total of 28 LGAs. In the second stage, we obtained the list of communities from the relevant authorities in the 28 selected LGAs and five communities in each of the selected LGAs using a simple random technique, with the aid of a random number generator, to give a total of 140 sampled communities. In the third stage, we developed a sampling frame of sorghum-growing households in each of the selected communities through a census and randomly selected 12 sorghum-growing households in each community, giving a total of 1680 households. However, 1677 sorghum-growing households out of the sampled 1680 provided the complete and needed information for the study. Also, these 1677 sorghum farmers cultivated 3308 plots in total.

The survey instrument was a structured questionnaire with modules on household demographic composition, physical capital, financial capital, social capital, technology adoption, input use and crop production, crop marketing, household expenditures and food security. Both household- and plot-level data were collected. The survey was implemented through computer-assisted personal interviewing software 'Open Data Kit (ODK)' and tablets to improve the efficiency of the data collection. A trained team of enumerators administered the survey, and highly experienced supervisors led the data collection quality control. For ethical consideration, we included an informed consent form to the introductory note of the questionnaire, and the survey team used it to obtain verbal consent on individual farmer's willingness to participate in the survey.

4 | Conceptual Framework and Estimation Strategy

4.1 | Conceptual Framework

Following other empirical studies on the adoption of agricultural technologies and the impact of adopting such technologies (Tufa et al. 2019; Abdoulaye et al. 2018), we model the decision of an individual sorghum-growing household to adopt (or not to adopt) an improved sorghum variety (ISV) using the random utility framework. The framework assumes that a sorghum farmer who seeks to maximise utility will consider adopting an ISV if the expected utility (e.g., productivity and net farm income) associated with the adoption of an ISV, U_a, is greater than the expected utility associated with the farmer not adopting an ISV, U_n. In this regard, we assume that a farmer will adopt an ISV if $I^* > 0$, where I^* represents the difference in expected utility between adoption and nonadoption of an ISV $(U_a - U_n)$. While I^* cannot be observed, it can be expressed as a function of observable covariates—farmer, household, farm, institutional and location characteristics, X_i and an error term, μ_i, as follows:

$$I^* = \beta D_i + \mu_i \quad with \quad I_i = \begin{cases} 1 & if \ I^* > 0 \\ 0 & otherwise \end{cases} \quad (1)$$

Where I_i is a binary variable that takes a value of 1 if a sorghum farm household adopts an ISV and 0 otherwise, and β is a vector of parameters associated with D_i (where D_i is the vector of the explanatory variables). An adopter of an ISV is defined as a sorghum farm household who cultivated one or more of the following ISVs: Samsorg 14, Samsorg 17 (SK5912), Samsorg 38 (NR-71176), Samsorg 39 (NR-71182), Samsorg 40 (ICSV 400), Samsorg 41 (ICSV 111), Samsorg 43 (SSV98002), Samsorg 44 (SSV20043), Samsorg 45 (improved Deko), Samsorg 46 (improved Zabuwa), Samsorg 47 (Zauna Inuwa), Samsorg 48 (Kaura Borno), Samsorg 49 (CF35.5), CSR-01 (Farfara ex-Kano), CSR-02 (Farfara ex-Katsina), CSR-03H, CSR-04H, PD86W15 and PD87W16 during the 2018 cropping season.

We hypothesise that the adoption of an ISV would lead to an increase in sorghum productivity and net farm income from sorghum production. This would mean that sorghum productivity and net farm income are based on an implicit function of the adoption of an ISV, I_i, a vector of control variables, X_i and an error term, v_i, as follows:

$$Y_i = \gamma_0 + \gamma_1 I_i + \gamma_2 X_i + v_i \quad (2)$$

Where Y_i represents the plot-level outcomes of interest, including sorghum productivity (yield), measured as the crop output

in kilogram per hectare (kg/ha), and sorghum net income, measured as the net crop value in Nigeria naira per hectare (NGN/ha), the latter is calculated as the sorghum income per hectare minus the total variable costs of sorghum production per hectare, that is, the costs of seeds, fertiliser, pesticides and hired labour. We used the natural logarithm of sorghum yield and net farm income as the dependent variables, expressed as functions of input use in natural log form, and household, farm, institutional and location variables.

An ordinary least squares (OLS) estimation of Equation (2) may lead to biased estimates of the causal effects of agricultural technology adoption if farm households are not randomly assigned into treatment and control groups, as in our study context. In this regard, estimating the impact of adopting ISVs on our outcomes of interest is nontrivial given our nonexperimental study context. Sorghum-producing households' adoption may be endogenous due to nonrandom self-selection into the group of adopters or nonadopters, which originates from observable and unobservable heterogeneity. In particular, unobservable characteristics (e.g., management experience, innate intelligence and propensity to innovate, etc.) of the sorghum-producing households may affect both the decision to ISVs and the outcomes of interest, resulting in endogeneity and inconsistent estimates (Wooldridge 2010). PSM is a well-known econometric used with observational data to establish causality when there is selection bias (see Mendola 2007). However, existing literature indicates that, while PSM can successfully address selection bias resulting from observable characteristics in impact evaluation studies, it is limited in terms of selection bias resulting from unobservable characteristics (Shiferaw et al. 2014; Wossen et al. 2017). In this study, we employ the ESR model to adequately address any potential selection bias or endogeneity issues that may arise from both observable and unobservable characteristics of the sampled sorghum-growing households.

4.2 | Endogenous Switching Regression (ESR)

Following similar impact evaluation studies (Kamara et al. 2022; Abdulai and Huffman 2014; Asfaw et al. 2012), we employed the ESR model to estimate the impacts of ISV adoption on the productivity and net income of the sampled sorghum-growing households. The econometric framework for ESR estimation follows two stages (Lokshin and Sajaia 2004). In the first stage, a probit regression is used to explain the probability of ISV adoption as expressed in Equation (1), which is the selection equation. In the second stage, the determinants of the outcomes of interest are estimated using an OLS regression, conditional on adoption—that is, adopter and nonadopter regimes. The two regimes are expressed with outcome Equations (3a) and (3b) for adopters (Regime 1) and nonadopters (Regime 2) of ISVs respectively.

Regime 1:

$$y_{1i} = \beta_1 X_{1i} + v_{1i} \qquad \text{if } I_i = 1 \tag{3a}$$

Regime 2:

$$y_{2i} = \beta_2 X_{2i} + v_{2i} \qquad \text{if } I_i = 0 \tag{3b}$$

The variables y_{1i} and y_{2i} are the outcomes of interest for the adopters and nonadopters of ISVs respectively. X_{1i} and X_{2i} represent a vector of observable household, farm, institutional and location characteristics for the adopters and nonadopters of ISVs respectively. β_1 and β_2 represent the vector of parameters associated with X_{1i} and X_{2i} respectively. v_{1i} and v_{2i} are the error terms associated with the adopter and nonadopter equations.

The estimation of β_1 and β_2 using OLS might lead to biased estimates because the expected values of v_{1i} and v_{2i} conditional on sample selection are likely to be nonzero, that is, μ_i in Equation (1) is likely correlated with v_{1i} and v_{2i} in Equations (3a) and (3b) respectively. The correlation of these parameters results in selection bias. The error terms in Equations (1), (3a) and (3b) have a trivariate normal distribution, with zero mean and nonsingular covariance matrix expressed as:

$$cov\left(\mu_i, v_{1i}, v_{2i}\right) = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \rho_{1\mu} \\ \sigma_{21} & \sigma_2^2 & \rho_{2\mu} \\ \sigma_{\mu 1} & \sigma_{\mu 2} & \sigma_\mu^2 \end{pmatrix} \tag{4}$$

Where σ_μ^2 is the variance of the error term in Equation (1), which is assumed to be equal to one since the β coefficients can be estimable to a scale factor (Maddala 1983). σ_1^2 and σ_2^2 are the error term variances in Equations (3a) and (3b), respectively, $\rho_{1\mu}$ is the covariance of μ_i and v_{1i} and $\rho_{2\mu}$ is the covariance of μ_i and v_{2i}. The covariance between v_{1i} and v_{2i} is not defined, as the outcomes of interest, y_{1i} and y_{2i} are observed separately (Maddala 1983). This implies that the expected values of the error terms in the outcome equations conditional on the sample selection are nonzero, given that the error term in the selection equation is correlated with the error terms in the outcome equations (Shiferaw et al. 2014; Asfaw et al. 2012). The expected values of the error terms in Equations (3a) and (3b) can be expressed as follows:

$$E\left(v_{1i} | I_i = 1\right) = \sigma_{1\mu} \frac{\emptyset\left(\beta X_i\right)}{\Phi\left(\beta X_i\right)} = \sigma_{1\mu} \lambda_{1i} \tag{5a}$$

$$E\left(v_{2i} | I_i = 0\right) = \sigma_{2\mu} \frac{\emptyset\left(\beta X_i\right)}{\Phi\left(\beta X_i\right)} = \sigma_{2\mu} \lambda_{2i} \tag{5b}$$

where $\emptyset(.)$ is the standard normal probability density function and $\Phi(.)$ is the standard normal cumulative density function. λ_{1i} and λ_{2i} are the inverse Mills ratios (IMR) estimated from the selection Equation (1). We included the generated IMRs as additional regressors in the outcome Equations (3a) and (3b) to correct for selection bias. We estimated the ESR using the full information maximum likelihood (FIML), which simultaneously estimates the selection and outcome equations to produce more efficient estimates of treatment effects compared with a two-step estimation procedure (Lokshin and Sajaia 2004). The estimation was implemented using the *movestay* command in Stata 16. In addition, FIML produces correlation coefficients ($\sigma_{1\mu}$ and $\sigma_{2\mu}$), whose signs and statistical significance have an essential economic interpretation. If the correlation coefficient, $\sigma_{1\mu}$ or $\sigma_{2\mu}$ differs significantly from zero, there is evidence of selection

bias due to unobservable factors (Abdulai and Huffman 2014). In terms of the sign, if $\sigma_{1\mu}$ or $\sigma_{2\mu} < 0$, there is a positive selection bias, suggesting that sorghum-growing households with above-average sorghum yield and net income have a higher likelihood to adopt ISVs, and vice-versa.

More robust identification of the ESR model necessitates the inclusion of at least one additional variable as an instrument in the selection model, even though the model can be identified by construction through nonlinearities in the selection model (Abdulai and Huffman 2014). The instrumental variable must have a strong correlation with the decision to adopt ISVs but have no direct effect on our outcomes of interest for it to be relevant. While we acknowledge that the choice of a relevant and valid instrument can be empirically challenging, we carefully motivate the suitability of our instrument from theory and practical considerations. The instrument considered in this study is the distance to seed market. This is a plausible instrument as we expect that farmers who are closer to seed markets have better access to improved crop varieties due to increased availability in those markets and are more likely to adopt ISVs. In the same vein, having access to seed markets is not likely to directly affect our outcomes of interest. Thus, any possible indirect effect of distance to seed market on our outcomes of interest will only arise through its effect on the decision to adopt ISVs. Some studies have used distance to seed market as an instrumental variable using the ESR model (Jaleta et al. 2018; Shiferaw et al. 2014). Based on Di Falco et al. (2011), we further conducted a falsification test to determine the instrument's relevance for our study context. The selection instrument is suitable as it is strongly correlated with the ISV adoption decisions of farmers at the 1% significance level (Tables 2 and 3) but not significantly correlated with yield and net income in the outcome equations of the nonadopters (Tables S1 and S2 in the Appendix S1).

The average treatment effect on the treated (ATT) is obtained by comparing the expected values of the outcomes of adopters in actual and counterfactual scenarios:

Adopters with the adoption of ISVs (actual scenario)

$$E(y_{1i}|X_{1i}=1) = \gamma_1 X_{1i} + \sigma_{1\mu}\lambda_{1i} \tag{6a}$$

Adopters without adoption of ISVs (counterfactual scenario)

$$E(y_{2i}|X_{1i}=1) = \gamma_2 X_{1i} + \sigma_{2\mu}\lambda_{1i} \tag{6b}$$

The ATT of adopters is the difference between (6a) and (6b), which is the average impact of the adoption of ISVs on the adopters' outcome variables.

$$ATT = E(y_{1i}|X_{1i}=1) - E(y_{2i}|X_{1i}=1) = X_{1i}(\gamma_1 - \gamma_2) + \lambda_{1i}(\sigma_{1\mu} - \sigma_{2\mu}) \tag{7}$$

To check for the robustness of the productivity and income impacts of the adoption of ISVs, we employ PSM (with the use of nearest-neighbour matching, radius matching and kernel matching techniques) and the inverse weighted probability regression adjustment (IPWRA), whose assumptions are quite different from those of ESR. However, both models (PSM and IPWRA) do not account for unobserved sources of selection bias. In addition, the PSM can produce biased estimates if the propensity score model is misspecified. The latter can be addressed in the IPWRA, as it can yield consistent estimates of treatment effects in the presence of misspecification of the treatment or outcome model, but not both (Wooldridge 2010). In other words, the IPWRA estimator has a doubly robust property. For conciseness, we do not go into the detailed specifics of these models. For a detailed overview of the PSM and IPWRA models, including the doubly robust property (see Manda et al. 2018; Wossen et al. 2017; Wooldridge 2010).

5 | Results and Discussion

5.1 | Descriptive Statistics of Dependent and Independent Variables

Table 1 shows the descriptive statistics of the outcome variables (sorghum yield and net income), the treatment variable (adoption of ISVs) and the explanatory variables (household, farm, institutional and location variables) by adoption status of the sorghum-growing households. Following previous empirical studies on agricultural technology adoption (Manda et al. 2020; Tufa et al. 2019; Abdoulaye et al. 2018; Abdulai and Huffman 2014; de Janvry et al. 1991; Feder et al. 1985), we selected relevant explanatory variables for our model. The mean age of an average sorghum farmer is about 46 years old, indicating that the farmers are still in their active age. With an average household size of 11 members, it means that sampled farmers have substantial family labour to call on in case of labour scarcity during the peak of farming activities, and it also means that farmers have higher food expenditure needs, necessitating households to adopt ISVs to improved their farm-level productivity. Also, an average farmer had about 7 years of formal education, implying that an average sampled farmer for our study can at least read or write. Most (83%) of the farmers had access to information about ISVs from different sources. On average, the farmers had one extension visit during the cropping season and obtained the credit of on average 10,345 NGN (29 USD). Their farm size is, on average, 1 ha with associated labour input of 27 man-days, seed rate of about 8 kg, herbicide of 1880 NGN (5 USD) and NPK inorganic fertiliser of 6970 NGN (19 USD). The wage rate is on average 780 NGN (2 USD) per man-day, and the price of sorghum grain is 7733 NGN (22 USD) per 100 kg bag.

Regarding biotic and abiotic shocks, about 10% of the farmers reported that they had severe disease infestation and about 7% reported that they experienced drought stress. In terms of location-related variables, the sorghum-growing households live on average 16 km away from the nearest seed market, 18 km away from the nearest fertiliser market and 19 km away from the nearest government extension office. A more significant proportion (about 50%) of the sorghum-growing households are in the northwest region.

On average, the adopters of ISVs had significantly larger years of formal schooling, household size, better access to sorghum varietal information, a larger livestock size, owned more household

TABLE 1 | Summary statistics of farm households by adoption status.

Variables	Pooled	Adopters	Nonadopters	Difference
Outcome variables				
Sorghum yield (kg/ha)	1440.420	2268.895	1162.256	1106.639***
Sorghum net income (NGN/ha)	57348.335	99571.583	43171.684	56399.899***
Treatment variable				
Adopt ISV (%)	25.100			
Explanatory variables				
Age of HHH (years)	45.890	46.167	45.797	0.37
Education of HHH (years of schooling)	6.820	8.457	6.271	2.186***
Household size (no. of HH members)	10.752	11.322	10.561	0.761***
Farming experience (years as independent farmer)	20.036	21.200	19.645	1.555***
Access to varietal information (%)	82.500	86.500	81.200	5.300***
Years in farmer association	7.674	3.486	9.080	−5.594
Number of extension contacts	1.213	1.298	1.185	0.113
Livestock (Tropical Livestock Unit, TLU)[a]	0.347	0.394	0.331	0.063***
Credit received (NGN/year)	10329.003	10124.279	10397.740	−273.461
Household asset index[b]	0.110	0.121	0.107	0.014***
Food expenditure (per capita expenditure on food)	15558.902	21653.900	13512.478	8141.422***
Farm size (ha)	1.093	1.165	1.069	0.096**
Herbicide cost (NGN/ha)	1883.894	3505.133	1339.555	2165.578***
NPK fertiliser cost (NGN/ha)	6970.755	6963.942	6973.043	−9.101
Male hired labour (total man-days/ha)	26.960	27.261	26.859	0.402
Seed rate (kg/ha)	7.877	7.704	7.935	−0.231**
Price of sorghum (NGN/100 kg bag)	7733.233	8164.663	7588.378	576.285***
Wage rate (NGN/man-day)	779.552	1001.041	705.186	295.855***
Soil fertility[c]	2.700	2.736	2.688	0.048*
Experienced disease stress (%)	10.200	10.300	10.200	0.100
Experienced drought stress (%)	7.100	7.900	6.900	1.000
Distance to seed market (km)	16.169	16.624	16.016	0.608
Distance to fertiliser market (km)	18.018	17.411	18.222	−0.811
Distance to government extension office (km)	19.94	30.677	16.335	14.342***
Northwest region (%)	50.800	51.900	50.400	1.500
Northeast region (%) %	35.800	35.900	35.800	0.100
Northcentral region (%)	13.400	12.200	13.800	−1.600
N	3308	832	2476	

Note: ***, ** and * denote 1%, 5% and 10% significance levels, respectively, NGN: 360 NGN (Nigerian Naira) is equivalent to 1 USD at the survey time.
Abbreviations: HH = household, HHH = Household head.
[a]Tropical livestock unit (TLU) = (Total cows × 0.7) + (total sheep × 0.1) + (total goats × 0.1) + (total chicken × 0.02).
[b]Household asset index = [0.01 × less expensive assets (e.g., radio) + 0.02 × expensive assets (e.g., smart phone) + 0.05 × very expensive assets (e.g., car)].
[c]Perception of soil fertility: poor soil fertility = 1, medium soil fertility = 2, high soil fertility =3, very high soil fertility = 4, [6]Perception of soil depth: shallow = 1, medium = 2, deep = 3.

TABLE 2 | Estimates of endogenous switching regression for sorghum yield specification.

Variable	Selection equation		Yield outcome equation (adopters)		Yield outcome equation (nonadopters)	
	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Age of HHH	−0.003	0.003	0.001	0.001	1.00E-03*	0.001
Education of HHH	0.132**	0.025	0.006	0.007	−0.007	0.007
Household size	0.888***	0.072	0.028	0.022	0.115***	0.020
Farming Experience	0.107***	0.035	0.007	0.009	−0.017*	0.010
Access to varietal infor.	0.212***	0.072	−0.013	0.021	−0.012	0.019
Years in association	−2.86E-04	3.38E-04	4.46E-04**	1.90E-04	1.36E-05	6.53E-05
Numb. of extension contact	0.001	0.010	−0.002	0.002	−0.002	0.003
Livestock	0.139*	0.073	0.072***	0.018	−0.007	0.021
Credit	−0.059	0.036	−0.019**	0.009	−0.011	0.010
Household asset index	2.342***	0.534	−0.263**	0.133	−0.166	0.152
Food expenditure	1.745***	0.103	−0.027	0.034	0.383***	0.027
Farm size	0.026	0.025	4.00E-03	5.00E-03	−3.00E-03	8.00E-03
Herbicide cost	5.25E-05***	6.26E-06	6.23E-07	1.05E-06	2.07E-06	2.27E-06
Fertiliser cost	4.95E-07	2.52E-05	−5.88E-06	5.60E-06	−1.97E-05***	7.41E-06
Male hired labour	−0.044	0.058	0.015	0.015	0.022	0.016
Seed rate	−0.023	0.035	−0.017*	0.009	−0.113***	0.010
Price of sorghum	2.07E-04***	2.24E-05	8.41E-06	5.38E-06	−5.11E-06	7.53E-06
Wage rate	−0.091***	0.026	0.012**	0.006	0.006	0.008
Soil fertility	0.016	0.036	0.022**	0.009	0.02**	0.010
Disease stress	−0.080	0.088	0.029	0.022	−0.05**	0.024
Drought stress	0.040	0.101	−0.003	0.025	0.026	0.029
Dist. to seed market	−0.034**	0.016				
Dist. to fertiliser market	0.012	0.017	−2.60E-04	0.004	0.021	0.005
Dist. to extension office	−0.062***	0.014	0.006*	0.004	−0.011**	0.004
Northwest region[a]	0.127	0.082	−0.002	0.021	−0.076	0.022
Northeast region[a]	0.175**	0.086	−0.001	0.023	0.006	0.023
Intercept	−10.606	0.734	7.719***	0.244	5.535***	0.205
Model diagnostics						
σ_a (adopters)			0.187***	0.005		
$\rho_{1\mu}$ (adopters)			0.036	0.1096		
σ_n (nonadopters)					0.364***	0.007
$\rho_{2\mu}$ (nonadopters)					−0.440***	0.066
Wald χ^2	61.120***					
Log pseudo-likelihood	−2193.763					
LR test of independent equations χ^2	17.02***					
N	3308		832		2476	

Note: ***, ** and * denote significance at 1%, 5% and 10% levels respectively.
[a]North central region is the reference region.

TABLE 3 | Estimates of endogenous switching regression for sorghum net income specification.

Variable	Selection equation		Net income equation (adopters)		Net income equation (nonadopters)	
	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Age of HHH	−0.003	0.003	0.001	0.001	0.002	0.001
Education of HHH	−0.13***	0.025	0.036***	0.012	−0.009	0.010
Household size	0.900***	0.072	−0.038	0.044	0.092***	0.028
Farming experience	0.121***	0.036	−0.024	0.017	−0.036***	0.014
Access to varietal info.	0.218***	0.072	0.026	0.037	−0.050*	0.027
Years in association	−3.32E-04	3.50E-04	4.19E-04	3.43E-04	−1.94E-05	9.30E-05
Num. of extension contact	−7.21E-05	0.010	−0.001	0.004	−1.37E-04	0.004
Livestock	0.134**	0.073	0.010	0.033	−0.016	0.030
Credit	−0.050	0.036	0.041**	0.017	−0.010	0.014
Household asset index	2.310***	0.535	−0.157	0.244	−0.423**	0.217
Food expenditure	1.734***	0.101	−0.039	0.072	0.336***	0.038
Farm size	0.033	0.025	0.011	0.010	0.002	0.011
Herbicide cost	5.41E-05***	6.32E-06	−8.52E-06***	2.03E-06	−1.30E-05***	3.20E-06
Fertiliser cost	7.78E-06	2.51E-05	−8.35E-06	1.01E-05	−4.33E-05***	1.06E-05
Male hired labour	−0.054	0.058	0.069***	0.026	0.009	0.023
Seed rate	−0.034	0.036	−0.15***	0.016	−0.187***	0.014
Price of sorghum	2.10E-04***	2.24E-05	1.34E-04	1.06E-05	1.62E-04***	1.06E-05
Wage rate	−0.091***	0.026	−0.005	0.011	−0.015	0.011
Soil fertility	0.011	0.037	0.032**	0.016	0.005	0.014
Disease stress	−0.093	0.089	−0.017	0.040	−0.103***	0.035
Drought stress	0.057	0.101	0.018	0.045	0.017	0.041
Dist. to seed market	−0.037**	0.016				
Dist. to fertiliser market	0.01	0.017	0.001	0.008	0.029***	0.007
Dist. to extension office	−0.06***	0.015	−0.002	0.007	−0.005	0.006
Northwest region[a]	0.138	0.082	−0.004	0.039	−0.054*	0.032
Northeast region[a]	0.191**	0.086	0.041	0.041	−1.78E-04	0.033
Intercept	−10.739***	0.738	10.364	0.513	8.932***	0.289
Model diagnostics						
σ_a (adopters)			0.336***	0.008		
$\rho_{1\mu}$ (adopters)			0.034	0.143		
σ_n (nonadopters)					0.529***	0.009
$\rho_{2\mu}$ (nonadopters)					−0.421***	0.060
Wald χ^2						
Log pseudo-likelihood						
LR test of independent equations χ^2						
N	3308		832		2476	

Note: ***, ** and * denote significance at 1%, 5% and 10% levels respectively.
[a]North central region is the reference region.

assets, had higher input prices (herbicides and wage rate) and received a higher sorghum price (Table 1). Only about 25% of the sampled households adopted an ISV, which suggests that the adoption of ISV is relatively low in Nigeria. This result is not too different from Ndjeunga et al. (2015), who reported that the share of sorghum area planted to ISVs is about 20% in Nigeria. In addition, the relatively low adoption of ISVs that we find is consistent with Smale et al. (2018), who reported that the adoption of ISVs is relatively low in Mali.

Concerning the outcome variables, the average sorghum yield of the pooled sample was 1.4 tons/ha, which is relatively low compared with the potential yield of over 3.5 tons/ha for some high-yielding varieties (Table 1). However, the adopters of ISVs had a significantly higher sorghum yield and net farm income than the nonadopters. While we find significant mean differences in the outcomes between the adopters and the nonadopters, we do not draw causal inferences about the adoption of ISVs because of the significant differences in observable characteristics between the two groups, which could lead to selection bias. We need to control for observed and unobserved heterogeneity between the adopters and the nonadopters to allow us to establish the causal effects of the adoption of ISVs (Wooldridge 2010).

5.2 | Endogenous Switching Regression (ESR) Estimates

The full information maximum likelihood (FIML) estimates of the ESR models for sorghum yield and net income specifications are presented in Tables 2 and 3 respectively. In the interest of brevity, we will only briefly discuss the determinants of ISV adoption, as our primary focus is to estimate the causal effects of the adoption of ISVs on sorghum yield and net income in the study area.

5.3 | Selection Equation: Determinants of Adoption

In Table 2, we present the results (the coefficients and standard errors) of the selection equation for sorghum yield in columns (1) and (2) respectively. We followed a similar approach to present the results of the selection equation for sorghum net income in Table 3. Given that the variables in the selection equations of both tables are the same, the results are qualitatively the same. The results show that covariates such as education of household head, household size, household asset index, access to varietal information, labour, seed rate, wage rate, herbicide cost, fertiliser cost, price of sorghum, distance to seed market, fertiliser market and extension service providers are significantly correlated with the probability of ISV adoption. Notably, our instrumental variable, distance to seed market, is negatively associated with the adoption of ISVs. This result is expected, as farmers who live further away from seed markets are more likely to have less access to improved seeds, which may inform their decisions to rely on traditional seeds. This finding is consistent with other empirical studies that find that spatial distribution of markets and services is strongly correlated with crop varietal adoption in

different parts of SSA (Manda et al. 2020; Abdoulaye et al. 2018; Shiferaw et al. 2014; Asfaw et al. 2012).

The educational level of the household head has a positive and significant association with the probability of adopting ISVs in line with the extant literature on drivers of agricultural technology adoption. This result is expected as more educated farmers can better seek, process and apply information about improved crop varieties (Takahashi et al. 2020; Jaleta et al. 2018; Abdulai and Huffman 2014). Household size has a positive and significant correlation with the probability of ISV adoption, and a plausible reason is that larger households are less likely to face labour constraints associated with agricultural technology adoption. This result is consistent with previous studies showing that household size is positively correlated with adopting improved crop varieties (Wossen et al. 2019; Jaleta et al. 2018). The price of sorghum is positively associated with ISV adoption. This suggests that the expectation of an attractive output price, which is an economic incentive, influences ISV adoption. This is consistent with Shiferaw et al. (2014) for improved wheat varietal adoption in Ethiopia and Asfaw et al. (2012) for improved pigeon pea varietal adoption in Tanzania. As expected, the household asset index is positively correlated with the adoption of ISVs, suggesting that wealthier households are more likely to adopt ISVs. This is plausible as wealthier households are less likely to face cash constraints associated with agricultural technology adoption (Foster and Rosenzweig 2010; Feder et al. 1985). This result is in line with the findings of previous studies on the effect of household asset endowment on varietal adoption (Khonje et al. 2018; Smale et al. 2018). Other variables positively correlated with ISV adoption livestock, farming experience, herbicide cost and food expenditure.

Distance to extension service and seed market are negatively correlated with the adoption of ISVs. This result is expected because farmers who live closer to government extension offices and input markets are more likely to have better access to information and improved seeds as well as complementary inputs, such as fertiliser, which would likely enhance their probability of adoption (Takahashi et al. 2020). This is consistent with other empirical varietal adoption studies that show the importance of distance to government extension offices (Martey et al. 2020; Khonje et al. 2015) and the role of distance from a farmer's house to the input market (Abdoulaye et al. 2018; Kassie et al. 2018). Other variables that are negatively correlated with ISV adoption include wage rate.

5.4 | Outcome Equations: Determinants of Sorghum Yield and Net Returns

Results from the outcome equations associated with sorghum yield and net income are presented in columns (3) to (6) of Tables 2 and 3 respectively. In general, our results show that some of the explanatory variables are significantly correlated with sorghum yield and net income and these relationships are notably different when the outcome equations of adopters and nonadopters of ISVs are compared. This indicates that the switching regression approach is better suited than a simple treatment effects model, as it accounts for both observed and

unobserved heterogeneities between the adopters and nonadopters (Amadu et al. 2020; Tufa et al. 2019; Kabunga et al. 2012). In particular, there are considerable variations in the association of education of household head, household size, livestock ownership, credit, fertiliser cost, seed rate and distance to extension market with sorghum yield of adopters and nonadopters. Similarly, covariates such as household size, education of household head, livestock ownership, household asset index, fertiliser and herbicide cost, labour, disease stress and distance to fertiliser market have differential associations with sorghum net income of adopters and nonadopters.

For adopters and nonadopters, household size has a positive and significant correlation with sorghum yield and net income, indicating that the more labour a family has the higher the associated farm productivity and net income. This is consistent with Kabunga et al. (2012), who find that the use of family labour is strongly correlated with maize yield and maize income of adopters and nonadopters of tissue culture banana in central and eastern Kenya. Concerning farm inputs, seed rate has a negative and significant association with the yield and net income of both adopters and nonadopters, while herbicide costs have a negative and significant association with the sorghum net income of both adopters and nonadopters. The latter is plausible when the costs of inputs are very high, mainly due to high transaction costs in the study area, as reported by Liverpool-Tasie et al. (2017). This result is partly consistent with Bairagi et al. (2020) that seed and fertiliser prices negatively affected the net rice income of the nonadopters of climate-resilient practices in Cambodia. As expected, the output price of sorghum is positively correlated with sorghum net income of both adopters and nonadopters, indicating that higher prices of sorghum increase the net income generated by the farmers.

We present the model diagnostics in the lower part of Tables 2 and 3. Notably, we find that the correlation coefficient, $\rho_{2\mu}$, a measure of the correlation between the error terms of the selection and outcome equations for the nonadopters, is significantly different from zero in both sorghum yield and net income specifications. This implies that there is evidence of selection bias due to unobservable heterogeneity, which lends credence to our use of ESR. The negative sign of the correlation coefficient indicates positive selection bias, implying that sorghum-growing households with higher-than-average yields and net income are more likely to adopt ISVs. This is consistent with previous studies that found positive selection bias (Amadu et al. 2020; Manda et al. 2020; Tufa et al. 2019; Abdoulaye et al. 2018). In addition,

the likelihood ratio tests for joint independence of the selection and outcome equations associated with the sorghum yield and net income specifications show that the equations are dependent (Tables 2 and 3). This implies that failure to reject the null hypothesis that the equations are not dependent would lead to biased estimates.

5.5 | Average Impacts of the Adoption of ISVs on Productivity and Net Returns

As discussed earlier, the differences in the mean value of sorghum yield and net returns between adopters and nonadopters shown in Table 1 do not necessarily represent the impact of ISV adoption due to systematic differences in observable and unobservable characteristics between the adopters and nonadopters. To consistently estimate the impacts of ISV adoption of ISVs on sorghum farmers' yield and net income, we rely on the average treatment effect on the treated (ATT), which accounts for selection bias arising from observable and unobservable heterogeneities. Table 4 shows the sorghum yield and net income predictions and the resulting ATT based on the estimates of the ESR model, as depicted in Equations (6a), (6b) and (7). The results show that the ATT estimate associated with sorghum yield is positive and significantly different from zero, implying that the adoption of ISVs significantly increases sorghum yield in the study area.

In addition, the ATT estimate represents a yield-increasing effect of about 13%, indicating that the adopters' sorghum yield increased by 13% due to the adoption of ISVs. This is expected as the improved varieties have high-yielding genetic potentials and are more tolerant to biotic and abiotic stresses, essential yield-limiting factors in the study area. The yield-increasing effect that we find is consistent with the findings of Smale et al. (2018) on the impact of ISVs in Mali. However, Smale et al. (2018) reported a much more significant yield effect of about 34%–35% (for ISVs that are not hybrids) and 79%–180% for sorghum hybrids. The more considerable yield impact of the adoption of ISVs in the Malian context could be due to differences in agro-ecological conditions and complementary management practices, among others, between the farming systems in Nigeria and Mali. In addition, this could be due to differences in estimation methods, particularly as the estimator employed by Smale et al. (2018) did not account for unobservable sources of selection bias, which could lead to an upward bias in the treatment effects. More empirical studies are necessary for other parts of SSA to allow a

TABLE 4 | Estimated average treatment effects based on endogenous switching regression.

| | Adoption decision | | | |
Outcomes	To adopt	Not to adopt	ATT	% gain
Sorghum yield	7.703	6.837	0.866***	12.66
	(0.002)	(0.006)	(0.006)	
Net sorghum income	11.577	9.917	1.660***	16.73
	(0.008)	(0.010)	(0.013)	

Note: *** denotes significance at 1% levels. Standard errors are reported in parentheses. Counterfactual predictions are in log forms, given that dependent variables are in log form.

better comparison of the yield impact of ISVs. Concerning the broader literature, our result is consistent with the growing empirical studies that have documented yield-increasing impacts of improved crop varieties among rural households in different parts of SSA (Bello et al. 2021; Martey et al. 2020; Oyinbo et al. 2019; Abdoulaye et al. 2018; Kassie et al. 2018; Khonje et al. 2018).

While we find considerable yield impacts of ISV adoption, reliance on yield gains without the associated economic returns only provides a partial picture of the impact of agricultural technology adoption (Michler et al. 2019). Regarding the net farm income, Table 4 shows that the adoption of ISVs led to a significant increase in net returns of the adopters by about 17%. This result is consistent with the findings of previous studies that have demonstrated that agricultural technology adoption can boost farm incomes (Bairagi et al. 2020; Manda et al. 2020; Tufa et al. 2019). This result is quite important, as the farm income channel is often cited as a pathway for improving the welfare of rural farming households, including reducing hunger and poverty (Ligon and Sadoulet 2018). This is particularly important for achieving the United Nations Sustainable Development Goals (SDGs 1 and 2).

Overall, given that sorghum is a multipurpose crop (for food, feed and cash) in our study area, our results suggest that the adoption of ISVs can improve the grain yield and net income of smallholder farmers, which are the direct effects of technology adoption that can potentially deliver indirect effects to the broader rural economy. This is particularly important given the low adoption rate of ISVs in the study area, which implies that there are considerable missing opportunities that sorghum-growing households can harness through the adoption of ISVs. While we do not explicitly analyse the indirect effects of ISV adoption, and cannot draw causal inferences about the indirect effects, empirical findings from Musara and Musemwa (2020) show that the adoption of ISVs improved food security among rural farming households in Zimbabwe. We note that more empirical studies may help to clarify the indirect effects of ISV adoption in Nigeria and other parts of SSA.

5.6 | Robustness Check

To check for the robustness of our main impact estimates presented in Table 4, we estimated other models, including PSM and inverse probability weighting regression adjustment (IPWRA). The latter is necessary as our primary impact estimates could be sensitive to the instrumental variable assumption of ESR (Shiferaw et al. 2014). The PSM method was analysed using three matching methods, nearest-neighbour matching (NNM), radius matching (RM) and kernel-based matching (KBM), to allow for further robustness of the observed effects. To begin, we check for the quality of the matching. Figures S1 and S2 in the Appendix S1 show a visual inspection of the distribution of the estimated propensity scores for the adopters and nonadopters of ISVs for yield and net returns respectively. Both figures show considerable overlap in the propensity score distribution of both ISV adopters and nonadopters, which implies that the common support condition has been satisfied.

Overall, the ATT estimates using the PSM and IPWRA estimation techniques are consistent with the estimates associated with the ESR approach, suggesting that the adoption of ISVs led to an increase in sorghum yield and net income of the adopters (Table 5). Table 5 shows that ISV adoption led to an increase in sorghum yield between 8% and 10% and an increase in net income between 5% and 7%. The latter is lower than the ATT estimates associated with the ESR approach, which could be due to the inability of the PSM and IPWRA estimation techniques to control for unobservable sources of selection bias.

6 | Conclusion

Using large household survey data from a sample of 1677 households with 3308 plots in the sorghum belt of Nigeria, we measure the impact of ISV adoption on productivity and net returns of smallholder sorghum farmers. We estimate ESR, which accounts for potential selection bias from observed and unobserved heterogeneity, and we perform robustness checks of our impact estimates. Our findings show that the rate of adoption

TABLE 5 | Robustness checks on sorghum yield and net income impacts.

| Outcomes | Estimator | Mean value of outcomes | | ATT | % gain |
		Adopters	Nonadopters		
Sorghum yield	NNM	7.710	7.092	0.618*** (0.026)	8.714
	RM	7.710	6.990	0.720*** (0.025)	10.3
	KBM	7.710	7.011	0.699*** (0.019)	9.97
	IPWRA	7.708	7.000	0.708***	10.114
Net income	NNM	11.591	11.023	0.568*** (0.038)	5.153
	RM	11.591	10.841	0.750*** (0.037)	6.918
	KBM	11.591	11.043	0.548*** (0.029)	4.962
	IPWRA	11.521	10.865	0.656***	6.038

Note: *** denotes significance at 1% levels. Standard errors are reported in parentheses.

of ISVs among sorghum growers is about 25%, which is relatively low. This suggests that despite the increasing investment in sorghum varietal improvement research and the resulting varietal turnover, it does not translate into widespread adoption of the ISVs among smallholder farmers. This low level of adoption raises concerns about the scalability of the ISVs in the study area. Among other factors, access to varietal information and distance to the seed market strongly explain the adoption of ISVs in the study area. This suggests that better access to varietal information about ISVs and better access to seeds would help to increase the adoption of ISVs. Thus, policymakers and development partners should increase investments in ISV dissemination to allow better access to information on the availability of the seeds, the varietal traits, the management practices associated with cultivating the seeds, where to source the seeds, the price of the seeds, the expected returns, among others. Also, there is a need for more collaborative efforts of the public and private sectors to strengthen the sorghum seed systems towards improving seed multiplications and ensuring that improved sorghum seeds are available within reach of smallholders at a more affordable price.

Our findings show that the adoption of ISVs leads to a 13% and 17% increase in sorghum yield and net returns of the adopters respectively. From a methodological perspective, we perform robustness checks using three matching techniques of PSM model and IPWRA model. The results confirm that the adoption of ISVs leads to a positive and significant effect on sorghum yield and net returns. In light of the relatively low adoption of ISVs, the sorghum yield and net returns-increasing effects of ISV adoption imply that there are considerable missing opportunities that sorghum-producing households can harness through widespread adoption of the improved varieties.

The policy implication is that increasing investments in promoting the widespread adoption of ISVs can boost productivity and farm incomes, potentially improving food security and household well-being. However, this requires prioritising varietal dissemination alongside breeding research to address the barriers to ISV adoption. In this regard, public and private sectors should collaborate to scale seed production, enhance extension services and strengthen market linkages through better storage, transport and agro-industry partnerships. Without these complementary efforts tailored towards widespread dissemination, the benefits of varietal improvement research will remain limited.

While this study provides valuable insights into the adoption and impacts of ISVs on productivity and income in Nigeria, we acknowledge some limitations of the study. First, the cross-sectional nature of the data limits the ability to capture long-term impacts and dynamic changes in ISV adoption and its effects. Longitudinal studies would help understand these dynamics better. Second, although the ESR model and robustness checks address selection bias, residual unobserved heterogeneity might still influence the results. Future research could explore advanced panel data methods to strengthen causal inference. Third, we do not consider the role of complementary policy incentives such as seed subsidies in promoting the adoption of ISVs. Future studies should examine the cost-effectiveness of different policy incentives in scaling ISVs.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets used in this study are available from the corresponding author on request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.