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Sustainable intensification technologies and farm performance: evidence from smallholder sorghum farmers in Nigeria

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ABSTRACT

The empirical literature on plot-level adoption of sustainable intensification technologies (SITs), as a package comprising improved crop varieties and good agronomic management practices is thin for dryland crops, such as sorghum. In this paper, we analyze the adoption and impacts of SITs on sorghum yield and net revenue using data from a sample of 1680 households and 3310 plots in the sorghum belt of Nigeria. Our estimates are based on a multinomial endogenous switching regression, which accounts for observable and unobservable sources of selection bias. We find a relatively low joint adoption of both improved sorghum varieties and good agronomic practices. In addition, we find that the adoption of only improved sorghum varieties and the joint adoption of both improved sorghum varieties and good agronomic practices led to a 56 and 102% increase in sorghum yield, respectively, and an 88 and 82% increase in net revenue, respectively. The yield and net revenue effects indicate that there are considerable missing opportunities that sorghum-producing households can harness through the adoption of SITs. Our findings reveal that policies tailored towards promoting the widespread adoption of SITs can lead to considerable productivity gains and economic returns for smallholder sorghum farmers towards improving their welfare.

1. Introduction

Agricultural productivity growth is widely considered an important pathway for addressing rural poverty and food insecurity as well as stimulating structural transformation in Sub-Saharan Africa (SSA) (Gollin et al., 2021; Ligon & Sadoulet, 2018; Otsuka & Muraoka, 2017). Yet, crop yields are on average low in SSA, including Nigeria, and lag far behind yields in other parts of the world (Suri & Udry, 2022). For instance, while sorghum is often touted as an important multipurpose crop – for food, cash and fodder in Nigeria, yields on farmers' fields are often less than 1 ton per hectare despite the potential of 3.5 tons per

hectare (Ajeigbe et al., 2018). Such low sorghum yields have been reported in other parts of SSA (Musara & Musemwa, 2020; Smale et al., 2018; Traore et al., 2017). The low yields are due to biotic and abiotic constraints, including erratic rainfalls, drought, poor soil fertility, pest and diseases, and poor agronomic management practices, among others (Ajeigbe et al., 2019; Mengistu et al., 2019; Mrema et al., 2017; Sebnie et al., 2020).

Given the rising population pressure and the limited opportunities for agricultural growth through cropland expansion in SSA, there is a

growing interest in expanding food production through agricultural intensification (Binswanger-Mkhize & Savastano, 2017; Droppelmann et al., 2017; Jayne et al., 2019). Although intensification, i.e. increasing crop yields on currently cultivated cropland is highly desirable, it has to be done sustainably by reducing its negative environmental impacts, which was a pitfall of the Asian Green Revolution (Burke et al., 2022; Jayne et al., 2019; Pingali, 2012; Pretty & Bharucha, 2014; Rockström et al., 2017). Thus, beyond the widespread adoption of intensification technologies such as high-yielding varieties and chemical fertilizers, as in the Green Revolution era, the adoption of complementary agronomic management practices can contribute to the sustainable intensification of cropping systems (Kotu et al., 2017; Jayne et al., 2019; Vanlauwe & Dobermann, 2020).

To boost the productivity of sorghum, the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) in collaboration with National Agricultural Research Systems and other partners, have developed sustainable intensification technologies (SITs) tailored to sorghum in West and Central Africa (Ajeigbe et al., 2019; Kante et al., 2019; Ndjeunga et al., 2015; Weltzien et al., 2018). The SITs include improved sorghum varieties (ISVs) with multi-stress tolerant traits and good agronomic practices (GAPs), such as tailored fertilizer use, planting density and planting time, etc. Several donor-funded projects and government-led interventions in northern Nigeria have helped in disseminating the ISVs and complementary GAPs required to maximize their varietal genetic potentials. Despite the notable development and dissemination efforts, there is limited evidence on the adoption and impacts of adopting the SITs.

Most previous studies that have documented the productivity and welfare impacts of agricultural technology adoption in different parts of SSA mainly focus on traditional crops, such as maize, cowpea, cassava, groundnut, and rice. In addition, most of the previous studies often focus on single agricultural technology adoption, largely on the adoption of improved crop varieties, despite the motivation for sustainable agricultural intensification technologies, as discussed in emerging empirical studies (e.g. Kotu et al., 2017; Marenya et al., 2020; Mellon Bedi et al., 2022). Single agricultural technology adoption, especially on crop varietal improvement has been documented for maize (e.g. Abdoulaye et al., 2018; Oyinbo et al., 2019), for cowpea (e.g. Alene & Manyong, 2006;

Manda et al., 2020) for cassava (e.g. Awotide et al., 2015; Wossen et al., 2019), for groundnut (e.g. Jelliffe et al., 2018; Kassie et al., 2010), and for rice (e.g. Arouna et al., 2017; Bello et al., 2020). Despite the considerable varietal improvement and agronomic management research for sorghum in SSA, empirical studies have only focused on the adoption and impacts of adopting ISVs – the few studies to our knowledge include Musara and Musemwa (2020) in Zimbabwe and Smale et al. (2018) in Mali. Thus, it remains unclear whether, and to what extent the joint adoption of ISVs and GAPs delivers productivity and welfare gains to sorghum-producing households.

In this paper, we analyze the adoption and *ex-post* impacts of the adoption of SITs in Nigeria. Specifically, we focus on the plot-level impacts of SITs adoption on productivity and net revenue of smallholder sorghum-producing households. We contribute to the literature in four ways. First, our paper contributes to the emerging literature on sustainable intensification of smallholder cropping systems in SSA by providing evidence on the adoption and drivers of SITs adoption for sorghum. In this sense, we build on the empirical studies that largely focused on SITs for maize in SSA (e.g. Kotu et al., 2017; Marenya et al., 2020; Mellon Bedi et al., 2022). Secondly, we provide rigorous evidence on the impacts of adopting SITs concerning an important multipurpose crop that has received limited attention in the extant literature on the impacts of agricultural technologies. In this way, we make the first attempt to document the productivity and net revenue impacts of SITs for sorghum and build on the few studies that only focused on ISVs in SSA (Musara & Musemwa, 2020; Smale et al., 2018). Relatedly, we contribute to the emerging empirical literature that addresses the impacts of agricultural technologies using the framework of multiple technology adoption decisions (e.g. Kassie & Muricho, 2018; Khonje et al., 2018; Marenya et al., 2020).

Thirdly, unlike the previous studies on the impacts of sorghum technologies in SSA and other studies on technology adoption and impacts that relied on a relatively small sample (e.g. Amadu et al., 2020; Bello et al., 2020; Oyinbo et al., 2019), our paper relies on a nationally representative household survey data from a sample of 1680 sorghum-producing households and 3310 plots in the sorghum belt of Nigeria. From the perspective of external validity, this improves the generalization of our findings across the entire sorghum belt of Nigeria. Lastly, we

control for potential selection bias arising from observable and unobservable heterogeneity using the multinomial endogenous switching regression model as our treatment effect estimation strategy. In addition, we perform a robustness check using augmented inverse probability weighting. From a methodological point of view, this is an improvement over empirical studies on the impacts of technology adoption that do not account for possible selection bias from unobservable characteristics (e.g. Kassie et al., 2010; Khonje et al., 2018; Manda et al., 2018).

2. Sorghum interventions in Nigeria

The collaborative efforts of ICRISAT and other international and national partners have resulted in the development and dissemination of ISVs and associated agronomic management practices in West and Central Africa (Kante et al., 2019; Weltzien et al., 2018; Ndjeunga et al., 2015). In Nigeria, ISVs have been developed for different agro-ecological zones over the years and the varieties possess different agronomic traits. A lot of the varieties have a high-yielding trait, with grain yield potentials of 2.5 to 3.5 t/ha, varieties, such as Samsorg 45, Samsorg 46, Samsorg 47, Samsorg 48, CSR-01, CSR-02, CSR-03 H, CSR-04 H, among others. Some of the traits of other ISVs include extra-early, early and medium maturity, high content of Fe and Zn, high stover, *Striga* tolerance and good malting qualities. Several donor-funded projects in Nigeria have directly and indirectly contributed to promoting these ISVs and associated agronomic management practices (fertilizer use, row spacing and planting date) through field days, demonstration trials, seed multiplication, extension services, capacity building of stakeholders, and strategic partnerships with seed companies and community-based organizations, etc. 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 the development of some varieties, such as Samsorg 45, Samsorg 46, Samsorg 47, Samsorg 48 and Samsorg 49. A few ongoing 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. The Federal Government of Nigeria through the Agricultural Transformation Agenda (ATA) (2012-2015) promoted the use of ISVs and GAPs in its bid 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) promoted the use of ISVs with associated GAPs, 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 nine States of Nigeria, including Jigawa, Sokoto, Kano, Kebbi, Katsina, Niger, Adamawa, Bauchi, and Gombe States (Figure 1). These States were selected because they have the highest level of sorghum production in Nigeria and are substantially representative of the sorghum belt (Ajeigbe et al., 2019). These states lie within the southern Guinea Savanna, northern Guinea Savanna, Sudan Savanna and Sahel savanna agro-ecological zones of Nigeria. The study is based on data from a comprehensive farm-household survey of sorghum-producing households in the sorghum belt of Nigeria.

We used a three-stage sampling design to select the sorghum-producing households for the study. In the first stage, we applied a probability proportional to size sampling to select 4 Local Government Areas (LGAs) each in 5 States (Kano, Katsina, Niger, Bauchi and Adamawa) and 2 each in 4 states (Sokoto, Kebbi, Jigawa and Gombe) giving a total of 28 LGAs.[1] In the second stage, we obtained the list of communities from the relevant authorities in the 28 selected LGAs and 5 communities were randomly selected in each of the selected LGA using a random number generator to give a total of 140 sampled communities. In the third stage, we developed a sampling frame of sorghum-producing households in each of the selected communities through the use of a census, and randomly selected 12 sorghum-growing households in each community giving a total of 1680 households. The survey instrument was a structured questionnaire, which had 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. 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 team of trained enumerators administered the survey with data collection quality

Figure 1. Map of the study area.

control by highly experienced supervisors. The survey was conducted between October to December 2019. During the survey, we collected data on plot, household, institutional, and location variables. For ethical consideration, we included an informed consent form to the introductory note for farmers on the purpose of the survey and the survey team used it to obtain verbal consent of each farmer's willingness to participate in the survey. In addition, the data were analyzed anonymously. The approval for this research was obtained from ICRISAT. The variables are described in detail in Table 1.

Table 1. Adoption combinations of sustainable intensification technologies.

SIT combination	Description
ISV_0GAP_0	Non-adoption of both good agronomic practices (GAPs) and improved sorghum varieties (ISVs)
ISV_0GAP_1	Adoption of only good agronomic practices (GAP)
ISV_1GAP_0	Adoption of only improved sorghum varieties (ISVs)
ISV_1GAP_1	Joint adoption of good agronomic practices (GAPs) and improved sorghum varieties (ISVs)

4. Conceptual framework and estimation strategy

4.1. Conceptual framework

Estimating the causal effects of the adoption of SITs is empirically challenging because of potential selection bias. For example, sorghum farmers' adoption may be endogenous due to non-random self-selection into the group of adopters or non-adopters, 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 adopt ISVs and the outcomes of interest, resulting in endogeneity and inconsistent estimates (Woolridge, 2010). While propensity score matching has been widely applied in empirical impact evaluation studies to deal with the issue of selection bias, it does not address selection bias arising from unobservable characteristics (Shiferaw et al., 2014; Wossen et al., 2017). To properly account for potential selection bias and

endogeneity arising from both observable and unobservable factors, we rely on the multinomial endogenous switching regression (MESR) as our main econometric approach. The MESR employs a selection correction method by computing an inverse Mills ratio (IMR) using the theory of latent factor structure and a truncated normal distribution, to correct for selection bias (Shiferaw et al., 2014). The MESR framework is modelled in two stages. In the first stage, farmers' choice of alternative technologies is estimated using a multinomial logit (MNL) model. The IMRs are calculated from the estimated probabilities in the MNL model. In the second stage, impacts of each combination of SITs are evaluated using OLS with IMRs as additional covariates, to account for selection bias from unobserved heterogeneity.

In our study context, we consider the adoption of SITs – ISVs and GAPs, which results in four possible technology adoption choices, as presented in Table 1. The first category represented by the notation ISV_0GAP_0 denotes the non-adoption of ISVs and/or GAPs at the plot level during the 2018 cropping season. The second category represented by the notation ISV_1GAP_0 denotes the adoption of only ISVs, given as plots that were cultivated with any of the following ISVs listed in Table A1 in the appendix during the 2018 cropping season. The third category represented by the notation ISV_0GAP_1 denotes the adoption of only GAPs, given as plots that were cultivated with at least two practices out of the following GAPs: application of NPK fertilizer, appropriate planting density measured by 75 cm ridges plant spacing and planting 1 week after the onset of rainfall. Lastly, the fourth category with the notation ISV_1GAP_1 denotes plots that were cultivated with an ISV and with at least two practices out of the GAPs.

4.2. Estimation strategy

4.2.1. Multinomial logit selection model (first stage)

The first stage of our econometric estimation is the use of a multinomial logit to estimate the determinants of SITs adoption. Embedded within the conceptual framework is the assumption that farmers' decision to adopt SITs is modelled within a random utility framework. Following Manda et al. (2021) and Khonje et al. (2018), we consider the latent model as follows:

$$U_{ji}^* = B_j X_{ji} + \varepsilon_{ji} \qquad (1)$$

U_{ji}^* denotes the indirect utility that is associated with the jth choice ($j = 1, \dots, 4$). There are four technology choices[2], with the first $j_1 = ISV_0GAP_0$, representing our reference category which is non-adoption. X_{ji} is the vector of observed exogenous variables comprising both plot and household characteristics while the error term ε_{ji} captures unobserved characteristics. B_j is a vector of parameters associated with X_{ji}. X_{ji} is assumed to not correlate with the random unobserved stochastic component of ε_{ji}. Although the utility of SITs adoption (U_{ji}^*) is not observable, we observe that the decision to adopt the combination of SITs will occur if its expected utility is relatively higher than other technology combinations.

$$U = \begin{cases} 1 \text{ if } U_{ji}^* > max_{k \neq 1}(U_{ki}^*) \text{ or } \varphi_{i1} < 0 \\ \quad \vdots \quad \vdots \quad \vdots \qquad\qquad \text{for all } k \neq j \\ M \text{ if } U_{ji}^* > max_{k \neq J}(U_{ki}^*) \text{ or } \varphi_{iJ} < 0 \end{cases} \quad (2)$$

Where $\varphi_{i1} = max_{k \neq M}(U_{ki}^* - U_{ji}^*) < 0$. If the assumption that ε_{ji} is independent and identically Gumbel distributed is met under the independence of irrelevant alternatives (IIA) hypothesis, then equation (1) leads to the MNL.

The probability that a farmer (i) will choose a technology (j) for the multinomial logit model is expressed as:

$$P_{ij} = \text{Pr}(\varphi_{ij} < 0 | X_i) = \frac{exp(X_iB_j)}{\Sigma_{k \neq 1}^J exp(X_iB_j)} \qquad (3)$$

Based on equation (3), consistent maximum likelihood estimates can be found.

4.2.2. Multinomial endogenous switching regression (second stage)

In the second stage, the MESR is employed to estimate the effect each technology choice (j) has on our outcome variables. The yield and net revenue regime can be expressed as:

$$\begin{cases} Regime\ 1: y_{i1} = \beta_1 z_{i1} + \mu_{i1} \text{ if } U = 1 \\ \quad \vdots \quad \vdots \quad \vdots \qquad\qquad j = 2, 3, 4 \\ Regime\ J: y_{ij} = \beta_j z_{ij} + \mu_{ij} \text{ if } U = J \end{cases} \quad (4)$$

In the equation above, y_{ij} represents the outcomes – sorghum yield and net revenue. Sorghum yield was measured as the crop output in kilogram per hectare (kg/ha), and net revenue was measured as the net crop value in Nigerian Naira per hectare

(NGN/ha). The latter was calculated as the sorghum revenue per hectare minus the total variable costs of sorghum production per hectare, i.e. the costs of seeds, fertilizer, pesticides and hired labour. z_{ij} represents a set of exogenous covariates, comprising plot, household, institutional, and location characteristics. The error term μ_{ij} are distributed such that the covariates do not correlate with the error term or $E(\mu_{ij}|x, z) = 0$ with a constant variance $var(\mu_{ij}|x, z) = \sigma_j^2$. For the parameters β_j to be consistently estimated, the MESR makes the following linearity assumption:

$$E(\mu_j|\varepsilon_{1i}\dots\varepsilon_{ji}) = \sigma_j\Sigma_{k \neq j}^j r_i(\varepsilon_{ji} - E(\varepsilon_{ji})) \quad (5)$$

The outcome variables are only observed if and only if one of the adoption combinations is used (Khonje et al., 2018; Manda et al., 2021). Some unobservable factors that influence the probability of adoption could also influence yield and net revenue, thus creating non-zero covariance between the error terms of the selection equation, ε_{ji} and the outcome equation, μ_{ij}. Therefore, the error terms in equation (4), conditional on the sample selection criterion, have non-zero expected values, and OLS estimates will not be consistent. Consistent estimation of β_j requires the inclusion of the selection correction terms of the choices in equation 5. Following Manda et al. (2021), the selectivity term or inverse mills ratio (IMR), computed from equation 2 can be defined as:

$$\hat{\gamma}_{ij} = \sum_{k \neq j}^j \rho_j[\frac{\hat{p}_{ki}\ln(\hat{p}_{ki})}{1 - \hat{p}_{ki}} + \ln(\hat{p}_{ki})]$$

Where ρ is the correlation between ε_{ji}, and μ_{ij}.

By constructing the correlation between the error terms in equations (3) and (4) at zero, equation (4) can be expressed as:

$$\begin{cases} \textit{Regime } 1: y_{1i} = \beta_1 z_{1i} + \sigma_1\hat{\gamma}_{i1} + v_{i1} \textit{ if } U = 1 \\ \qquad\qquad \vdots \quad \vdots \qquad\qquad\quad j = 2, \ 3, \ 4 \ (6) \\ \textit{Regime } J: y_{ij} = \beta_j z_{ij} + \sigma_j\hat{\gamma}_{ij} + v_{ij} \textit{if } U = J \end{cases}$$

Where σ is the covariance between ε_{ji}, and μ_{ij}. While v_{ij} is the error term with an expected value of zero.

More robust identification of the MESR model requires 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 non-linearities in the selection model (Abdulai & Huffman, 2014; Lokshin & Sajaia, 2004).

For an instrumental variable to be relevant in our study setting, it must have a strong correlation with the decision to adopt SITs but have no direct effect on our outcomes of interest. 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 instruments considered in this study are access to information on SITs, extension contact and distance to the nearest seed market. These are plausible instruments as we expect that farmers with access to information on SITs and better extension contact are more likely to be better informed about the technologies and may be more likely to adopt the technologies. This is consistent with the idea that relaxing information constraints about the availability, technical know-how and expected benefits of agricultural technologies can allow for better-informed decision-making (Conley & Udry, 2010; Magruder, 2018; Suri & Udry, 2022). In addition, we expect that farmers that are located closer to seed markets are more likely to have better physical access to SITs and may be more likely to adopt the technologies. On the other hand, better access to information on SITs, extension contact, and seed market are not likely to directly affect our outcomes of interest. Thus, any possible indirect effect of these instruments on our outcomes of interest will only arise through their effects on the decision to adopt SITs. In practice, these instruments have been used by previous studies in the impact evaluation literature (e.g. Abdoulaye et al., 2018; Di Falco et al., 2011; Olagunju et al., 2020; Shiferaw et al., 2014). Furthermore, we conducted a falsification test following Di Falco et al. (2011) to determine the validity of the instruments for our study context. The instruments are jointly significant in explaining the adoption of SITs (table 3) but not the yield and net revenue outcomes of the non-adopters (see appendix Tables A2 and A3).[3]

4.2.3. Estimation of average treatment effects
The MESR allows us to derive the expected actual and counterfactual outcomes (yield and net revenue). Following empirical studies (Manda et al., 2021; Marenya et al., 2020; Khonje et al., 2018), the expected yield and net revenue under the actual scenario for each technology combination are computed as follows:

$$E(y_{ij}|U = j, z_{ij}|\hat{\gamma}_{ij}) = \beta_j z_{ij} + \sigma_j\hat{\gamma}_{ij} \quad (7a)$$

While the counterfactual choice for each outcome is computed as

$$E(y_{i1}|U = j, z_{ij}|\hat{\gamma}_{ij}) = \beta_1 z_{ij} + \sigma_1 \hat{\gamma}_{ij} \qquad (7b)$$

The average treatment effect which measures the impact of the use of SITs on yield and net revenue is the difference in expected outcomes between equations 7a and 7b. Which is given as:

$$ATT = E(y_{ij}|U = j, z_{ij}|\hat{\gamma}_{ij}) - E(y_{i1}|U = j, z_{ij}|\hat{\gamma}_{ij})$$
$$= z_{ij}(\beta_j - \beta_1) + \hat{\gamma}_{ij}(\sigma_j - \sigma_1) \qquad (8)$$

This method suggests that unobserved factors have differential effects on adopters and non-adopters hence taking the differences in effects, i.e. $\sigma_j - \sigma_1$, while holding $\hat{\gamma}_{ij}$ constant ensures that the effects of unobservables are cancelled out. To check for the robustness of MESR, we employ the augmented inverse probability weighting (AIPW). While the AIPW controls for only observable heterogeneity, it is still necessary as our primary impact estimates using MESR could be sensitive to the instrumental variable assumption (Shiferaw et al., 2014).

5. Results and discussion

5.1. Summary statistics

The summary statistics of the explanatory variables (household, farm, institutional and location variables) of the sorghum-producing households by adoption are presented in Table 2. Based on the theory of farm-household decision-making under imperfect markets and previous studies on agricultural technology adoption, we selected relevant explanatory variables (e.g. Abdulai & Huffman, 2014; de Janvry et al., 1991; Kassie et al., 2018; Manda et al., 2020; Tufa et al., 2019). The farmers are on average 45 years old, have about 7 years of formal schooling, their spouses have about 4 years of formal schooling and they have on average, a household size of about 11 persons. The large majority (83%) of the farmers had access to information about improved sorghum varieties from different sources. On average, the farmers had one extension visit during the cropping season and obtained credit of on average 10329 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 1883 NGN (5 USD) and NPK fertilizer of 6970.76 NGN (19 USD). The wage rate is on average 827.59 NGN (2 USD) per

man-day and the price of sorghum grain is on average 7733 NGN (21 USD) per 100 kg bag. In terms of biotic and abiotic shocks, about 10% of the farmers reported that they had serious disease infestation and about 7% reported that they experienced drought stress. In terms of location-related variables, the sorghum-producing households live on average 18 km away from the nearest seed market, 16 km away from the nearest fertilizer market and 19 km away from the nearest government extension office. A larger proportion (about 50%) of the sorghum-producing households are in the north-west region.

5.2. Adoption of SITs and associated yield and net revenue

Table 3 shows the plot-level adoption of SITs and the associated yield and net revenue of the four categories. Results show that about 59% of the plots were cultivated without any of the technologies (ISV_0-GAP_0), which indicates that a larger share of the sorghum plots was cultivated without an ISV and/or GAPs despite the investment in research and dissemination of sustainable intensification technologies. About 16% of the plots had only good agronomic practices ($ISV_0 GAP_1$), and 3% had only improved varieties ($ISV_1 GAP_0$). The combined adoption of improved sorghum varieties and good agronomic practices ($ISV_1 GAP_1$) at the plot level was about 22%. The results indicate that the combined uptake of improved sorghum varieties and good agronomic practices is relatively low in the study area.

With respect to the outcome variables, the adopters of both technologies ($ISV_1 GAP_1$) had a higher sorghum yield and net revenues than the other categories. While we find notable mean differences in the outcomes between the four categories, we do not draw causal inferences about the adoption of SITs because of the significant differences in observable characteristics between the various categories, which could lead to selection bias. We need to control for observed and unobserved heterogeneity between the various categories to allow us to establish the causal effects of the adoption of SITs (Woolridge, 2010).

5.3. Factors explaining the adoption of sustainable intensification technologies (SITs)

Table 4 shows the marginal effects of the determinants of SITs. The covariates that have a positive

Table 2. Summary statistics of household- and plot-level characteristics.

		Pooled (N = 3310)	ISV_0GAP_0 (N = 1985)	ISV_0GAP_1 (N = 520)	ISV_1GAP_0 (N = 92)	ISV_1GAP_1 (N = 740)
Age of HH	Age of HH (years)	45.89 (11.93)	45.94 (12.08)	45.24 (11.76)	46.23 (11.21)	46.16 (11.72)
Years of education HH	Years of formal schooling of HH	6.82 (5.19)	6.18 (4.99)	6.61 (4.84)	10.11 (5.25)	8.25 (5.5)
Years of education spouse	Years of formal schooling of spouse	3.78 (4.59)	3.97 (4.61)	4.84 (4.62)	5.55 (5.78)	2.31 (3.93)
Household size	Total members in a household	10.75 (5.76)	10.79 (5.99)	9.68 (4.80)	11.99 (5.85)	11.24 (5.69)
Awareness of SITs	Aware of SITs for more than 3 years (1 = yes, 0 = otherwise)	0.34 (0.47)	0.49 (0.50)	0.49 (0.50)	0.49 (0.50)	0.45 (0.50)
Extension contact	Received agricultural extension service/training during the 2018 cropping season (1 = yes, 0 = otherwise)	0.83 (0.38)	0.78 (0.41)	0.93 (0.25)	0.89 (0.31)	0.86 (0.34)
TLU	Tropical livestock unit (TLU) = (Total cows * 0.7) + (total sheep *0.1) + (total goats * 0.1) + (total chicken *0.02)	0.35 (0.37)	0.33 (0.36)	0.35 (0.37)	0.28 (0.33)	0.41 (0.39)
Credit	Total credit borrowed during the 2018 cropping season (NGN)	10329 (5514.85)	10392.08 (5532.11)	10419.04 (5524.88)	9940.22 (5049.36)	10147.16 (5521.93)
Price of sorghum	Price of 100 kg bag of sorghum (NGN)	7733.23 (1172.81)	7583.76 (1010.87)	7605.77 (1040.77)	7500 (1084.35)	8247.3 (1485.04)
Household assets index	Index of household asset: 0.01*minor assets (e.g. radio) + 0.02*costly household assets (e.g. smart phone) + 0.05* costly bulky assets (e.g. car)	3.93 (1.65)	3.94 (1.65)	3.97 (1.59)	4.25 (1.63)	3.84 (1.7)
Wage rate	Wage of hired labour per day (NGN)	827.59 (293.23)	846.12 (295.59)	879.9 (293.38)	634.78 (168.5)	765.77 (280.01)
Soil fertility	Perception of soil fertility: 1 = poor soil fertility, 2 = medium soil fertility, 3 = high soil fertility, 4 = very high soil fertility.	2.70 (0.73)	2.69 (0.73)	2.69 (0.72)	2.47 (0.58)	2.77 (0.76)
Farm size	Total farm cultivated in hectares	1.09 (1.05)	1.06 (0.98)	1.09 (0.8)	1.36 (1.52)	1.14 (1.28)
Soil depth	Perception of soil depth: 1 = shallow, 2 = medium, 3 = deep.	1.98 (0.54)	1.99 (0.54)	1.98 (0.52)	1.96 (0.49)	1.95 (0.55)
Male hired labour	Total male labour used per hectare	26.96 (12.86)	26.74 (12.56)	27.31 (13.61)	27.21 (11.83)	27.27 (13.22)
Seed rate	Total kilogram of seed planted per hectare	7.88 (2.51)	7.88 (1.84)	8.14 (4.78)	7.93 (1.85)	7.68 (1.65)
Herbicide cost	Cost of herbicides per litre (NGN)	1883.89 (4734.39)	1374.87 (3507.89)	1206.58 (2643.82)	1745.35 (4101.39)	3723.92 (7509.71)
Fertilizer cost	Cost of NPK fertilizer per bag (NGN)	6970.76 (1039.43)	6987.23 (955.49)	6919.62 (1085.52)	6967.39 (882.69)	6963.51 (1222.26)
Distance to seed dealer	Distance to nearest seed dealer (km)	18.02 (21.74)	18.81 (21.67)	16.02 (23.18)	12.39 (21.27)	18.04 (20.76)
Distance to fertilizer dealer	Distance to nearest fertilizer dealer (km)	16.17 (20.21)	16.08 (20.02)	15.78 (20.1)	11.4 (14.54)	17.27 (21.3)
Distance to extension office	Distance to nearest extension office (km)	19.94 (19.62)	16.62 (17.57)	15.25 (16.89)	23.46 (20.75)	31.57 (21.71)
Crop disease stress	Farmer experienced crop disease on the sorghum plot (1 = yes, 0 = otherwise)	0.10 (0.30)	0.10 (0.30)	0.10 (0.30)	0.12 (0.33)	0.10 (0.30)
Drought shock	Farmer experienced drought on the sorghum plot (1 = yes, 0 = otherwise)	0.07 (0.26)	0.07 (0.25)	0.08 (0.27)	0.07 (0.25)	0.08 (0.27)
North West	Farmer is resident in North-West geopolitical zone Nigeria (1 = yes, 0 = otherwise)	0.51 (0.5)	0.52 (0.5)	0.45 (0.5)	0.36 (0.48)	0.54 (0.5)
North East	Farmer is resident in North-East geopolitical zone Nigeria (1 = yes, 0 = otherwise)	0.36 (0.48)	0.34 (0.47)	0.42 (0.49)	0.54 (0.5)	0.34 (0.47)

Note: HH = household head, NGN: 360 NGN (Nigerian Naira) is equivalent to 1 USD at the survey time. Standard deviation is reported in parentheses

Table 3. Adoption of SITs and associated yield and net revenue.

	Frequency (N = 3310)	Adoption (%)	Yield (kg/ha)	Net Revenue (NGN/ha)
ISV_0GAP_0	1958	59.15	1169.15 (389.65)	43867.96 (32562.67)
ISV_0GAP_1	520	15.71	1136.29 (394.69)	40549.94 (28320.36)
ISV_1GAP_0	92	2.78	1829.39 (358.89)	94402.08 (37051.83)
ISV_1GAP_1	740	22.36	2323.54 (344.20)	100214.28 (37866.20)

Note: standard deviations are reported in parentheses

Table 4. Marginal effects of determinants of SITs adoption using multinomial logistic regression.

	ISV_0GAP_1 (N = 520)	ISV_1GAP_0 (N = 92)	ISV_1GAP_1 (N = 740)
Age of HH	1.33E-03	−4.11E-04	−1.08E-03
	(6.11E-04)	(2.99E-04)	(6.79E-04)
Years of education HH	3.91E-03	−0.01***	−0.01
	(0.01)	(3.62E-03)	(0.01)
Years of education spouse	0.03***	0.01***	0.07****
	(0.01)	(3.78E-03)	(0.01)
Household size	−0.06***	0.02***	0.04***
	(0.01)	(0.01)	(0.01)
Extension contact	0.10***	0.02***	0.10***
	(0.01)	(0.01)	(0.01)
Aware of SITs	0.13***	0.01	0.04***
	(0.02)	(0.01)	(0.02)
TLU	0.02	−0.01	0.06***
	(0.02)	(0.01)	(0.02)
Credit	0.01	−7.15E-04	−0.01
	(0.01)	(3.88E-03)	(0.01)
Price of sorghum	1.20E-05**	6.00E-06**	7.10E-05***
	(5.00E-06)	(3.00E-06)	(5.00E-06)
Household assets index	4.55E-03	1.40E-03	−7.31E-03**
	(3.83E-03)	(1.67E-03)	(4.11E-03)
Wage rate	0.05***	−6.06E-03***	−0.03***
	(0.01)	(2.09E-03)	(0.01)
Soil fertility	−1.78E-03	−1.40E-02***	2.00E-02**
	(8.39E-03)	(4.21E-03)	(9.20E-03)
Farm size	−7.09E-04	6.34E-03***	−9.55E-04
	(6.04E-03)	(2.04E-03)	(6.28E-03)
Soil depth	−1.29E-03	7.55E-04	−0.02
	(0.01)	(0.01)	(0.01)
Male hired labour	0.01	2.43E-03	1.82E-03
	(0.01)	(0.01)	(0.01)
Seed rate	0.03***	−0.01***	−0.01
	(0.01)	(3.78E-03)	(0.01)
Herbicide cost	−4.00E-06**	3.54e-07	−1.50E-05
	(2.00E-06)	(7.02E-07)	(1.00E-06)
Fertilizer cost	−1.00E-05*	−2.00E-06	−3.00E-06
	(6.00E-06)	(3.00E-06)	(6.00E-06)
Crop disease stress	7.37E-03	5.41E-03	−0.03
	(0.02)	(0.01)	(0.02)
Drought shock	0.01	−6.24E-03	0.01
	(0.02)	(0.01)	(0.03)
Distance to seed dealer	−0.02***	−4.72E-03**	−6.72E-03*
	(3.74E-03)	(1.80E-03)	(3.97E-03)
Distance to fertilizer dealer	−2.43E-03	−2.85E-03	6.93E-03
	(3.91E-03)	(1.90E-03)	(4.29E-03)
Distance to extension office	0.01**	−1.94E-03	−1.52E-02**
	(3.36E-03)	(1.51E-03)	(3.60E-03)
North West[1]	−0.02	−8.62E-04	0.04**
	(0.02)	(0.01)	(0.02)
North East[1]	3.78E-03	0.02**	0.04*
	(0.02)	(0.01)	(0.02)
Joint significance of instrumental variables: χ^2 (9)	276.40***		

Note: ISV_0GAP_0 is the reference category, [1]North Central is the reference level, standard errors are reported in parentheses, ***, ** and * denote significance at 1%, 5% and 10% levels respectively.

and significant influence on the probability of adopting only good agronomic practices (ISV_0GAP_1) include years of spousal education, extension contact, awareness of SITs, wage rate and seed rate. Distance to seed dealer, household size, fertilizer costs and herbicide costs are negatively correlated with the probability of adopting GAPs.

The factors that have a positive and significant influence on the probability of adopting only improved sorghum varieties (ISV_1GAP_0) include years of spousal education, household size, sorghum price, extension contact and farm size. In addition, distance to seed dealer and labour wage rate have a negative influence on the adoption of only ISVs.

The factors that are positively associated with the joint adoption of ISVs and GAPs (ISV_1GAP_1) include household size, extension contact, years of spousal education, awareness of SITs, tropical livestock unit, the price of sorghum, soil fertility, and the location variables. Distance to a seed dealer and distance to an agricultural extension office is negatively correlated with the joint adoption decision.

Education of spouse is positively and significantly correlated with the adoption of SITs, including individual and joint adoption of ISVs and GAPs. This finding is consistent with Mutenje et al. (2016) who reported that a spouse's education is one of the important factors that shape agricultural technology choices within households in Malawi. Even in conservative settings, such as Bangladesh, reported spousal education as a key determinant in the adoption of improved management practices.

Household size is another significant determinant of SITs. It has a positive influence on the adoption of only ISVs and the combined adoption of ISVs and GAPs. This is consistent with the findings of previous technology adoption studies (Chandio & Yuansheng, 2018; Ruzzante et al., 2021). This result is logical because larger households can rely on family labour to overcome labour constraints that limit agricultural technology adoption (Suri & Udry, 2022).

Extension contact has a positive and significant influence on all combinations (ISV_0GAP_1, ISV_1GAP_0, ISV_1GAP_1) of SITs. This is expected, as farmers who are frequently visited by extension agents are more likely to be better informed about the benefits of SITs and may be more likely to adopt the technologies. Numerous empirical studies have documented similar effects of extension contacts on agricultural technology adoption (Ojo & Baiyegunhi, 2020; Takahashi et al., 2020).

Awareness of SITs has a positive and significant correlation with the adoption of SITs. This makes sense because for farmers to adopt any agricultural technology, the first-order condition is awareness of the technology (Conley & Udry, 2010; Foster & Rosenzweig, 1995; Magruder, 2018). This result is consistent with several studies on agricultural technology adoption in SSA (e.g. Khonje et al., 2018; Marenya et al., 2020).

The price of sorghum has a positive and significant correlation with the adoption of ISVs and the joint adoption of ISVs and GAPs. This suggests that farmers are sensitive to the output price of sorghum and the expectation of a favourable price incentivizes the uptake of SITs. Recent studies such as Mottaleb (2018) have demonstrated the importance of price on agricultural technology adoption.

Labour wage rate is negatively associated with the adoption of ISVs and the joint adoption of ISVs and GAPs. The negative influence of labour wage is expected because an increase in labour wage could translate into limited investment in SITs. However, the results also show that wage rate is positively correlated with adopting only GAPs, which is in agreement with Rahman and Chima (2018) who found a positive and significant influence of labour wage and ploughing price on pesticide use in southeastern Nigeria. This is possible because the use of SITs could generate high returns that can offset high labour costs.

Fertilizer and herbicide costs have negative and significant influence on the probability of adopting GAPs. This is logical as it would be more difficult to adopt GAPs when the prices of inputs are high, which suggests that when the price of these inputs is high, farmers will likely grow ISVs without complementary farm inputs. The result is consistent with studies that have reported that improved technology adoption is influenced positively by complementary input use (Fischer & Qaim, 2012; Kabunga et al., 2012).

Farmers' perception of low soil fertility is negatively associated with the adoption of ISVs, suggesting that farmers who perceive their soil fertility to be low or inadequate are less likely to adopt ISVs. This could be explained in part by risk aversion behaviour of farmers, especially if farmers perceive that ISVs may not yield better outcomes due to the perceived inadequacy of their soil nutrients. In such cases, risk-averse farmers are more likely to retain traditional sorghum varieties that they are more familiar with and have a track record of performance in their specific soil

conditions (Spiegel et al., 2021). Another potential explanation is liquidity constraint. To achieve high yields, ISVs typically require complementary inputs, such as fertilizer, which is costly. Thus, farmers with limited financial resources to purchase complementary inputs may be less likely to adopt ISVs (Jones-Garcia & Krishna, 2021). Consequently, in the presence of cash constraints to purchase fertilizer, farmers' perceived low soil fertility could deter them from adopting ISVs. This result is similar to Meshesha et al. (2022) who reported a negative relationship between the perception of soil fertility and the adoption of climate-smart agricultural practices in Ethiopia.

Distance to seed and fertilizer market and distance to extension service are negatively correlated with the joint adoption of ISVs and GAPs. In addition, distance to the nearest seed dealer has a negative and significant influence on adopting only GAPs and only ISVs. This result is consistent with other studies that have also reported a negative influence of distance to input market on the adoption of agricultural technologies (Kabir et al., 2017; Takahashi et al., 2020). Farmers that are further away from input markets may have less access to crucial inputs, such as improved seeds and complementary technologies, which could result in a lower propensity to adopt SITs.

Residing in the northeast is positively correlated with the adoption of only ISVs. Previous studies (e.g. Kabunga et al., 2012; Abdulai & Huffman, 2014) have also reported that location-related variables are significant in determining the adoption of improved agricultural technologies. Location variables are important due to heterogeneities in markets, infrastructure and levels of socioeconomic development across regions, which can affect technology adoption.

5.4. Average impacts of the adoption of SITs on yield and net revenues

As discussed earlier, the simple mean differences in sorghum yield and net revenues that we show in Table 3 do not necessarily represent the impact of SITs adoption, due to systematic differences in observable and unobservable characteristics between the adopters and non-adopters. To consistently estimate the yield and net revenue impacts of SITs adoption, we rely on the average treatment effect on the treated (ATT) derived from the MESR model, which accounts for selection bias arising from observable and unobservable heterogeneities. Table 5 shows the sorghum yield and net revenues predictions and the resulting ATT based on the estimates of the MESR model, as depicted in equations 7a, 7b and 8.

The results show that the ATT estimate associated with sorghum yield is positive and significantly different from zero for the adopters of only ISVs and the adopters of both ISVs and GAPs, which implies that the adoption of ISV_1GAP_0 and ISV_1GAP_1 significantly increases sorghum yields in the study area. Specifically, the ATT estimate of the adopters of only ISVs represents a yield-increasing effect of about 56%, which indicates that their sorghum yield increased by 56%, as a result of the adoption of improved sorghum cultivars. The yield-increasing effect that we find is consistent with the findings of a related study on the impact of ISVs in Mali (Smale et al., 2018). However, Smale et al. (2018) reported a much larger yield effect of about 79%–180% for the adopters of sorghum hybrids and a relatively smaller effect of about 34%–35% (for improved sorghum varieties that are not hybrids). The adoption of both ISVs

Table 5. Estimated treatment effects based on the MESR model.

Outcomes		To adopt (j = 2,3,4)	Not to adopt (j = 1)	ATT	Gain (%)
		Adoption decision			
Sorghum yield	ISV_0GAP_1	1070.73	1097.03	−26.30***	−2.40
		(7.36)	(6.72)	(5.38)	
	ISV_1GAP_0	1818.22	1162.04	656.18***	56.47
		(37.76)	(22.25)	(49.05)	
	ISV_1GAP_1	2298.20	1136.60	1161.61***	102.20
		(3.97)	(8.21)	(7.70)	
Sorghum net revenue	ISV_0GAP_1	51558.98	51618.63	−59.65	−0.12
		(580.18)	(635.75)	(456.52)	
	ISV_1GAP_0	108729.83	57785.91	50943.92***	88.16
		(3680.07)	(2118.57)	(3136.21)	
	ISV_1GAP_1	111752.38	61299.68	50452.70***	82.30
		(1012.84)	(775.96)	(476.47)	

Notes: Standard errors reported in parentheses, *** denote significance at 1% level

and GAPs led to about a 100% increase in yield, which shows the combination of both technologies doubled the yield of sorghum growers. This is expected as the high-yielding genetic potentials of improved crop varieties are better optimized when combined with optimal agronomic practices such as row spacing, planting date and fertilizer application. This aligns with Jayne et al. (2019) who argued that complementary management practices are necessary to improve yield responses. Our result is consistent with the growing empirical studies that have documented the yield-increasing effect of SITs among rural households in different parts of SSA (e.g. Mellon Bedi et al., 2022; Marenya et al., 2020; Kotu et al., 2017).

While we find considerable yield impacts of SITs 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). In terms of the net revenue, Table 4 shows that the adoption of improved variety alone (ISV_1GAP_0) led to a significant increase in net revenues of the adopters by about 88.16%. Those who adopted both ISVs and GAPs (ISV_1GAP_1) had an increase in their incomes by approximately 82.30%. This result is consistent with the findings of previous studies that have demonstrated that agricultural technology adoption raises farm incomes of rural households (e.g. Abdulai & Huffman, 2014; Manda et al., 2020; Tufa et al., 2019). This result is quite important, as farm income channel is often cited as a pathway for improving the welfare of rural farming households, including reduction of hunger and poverty (Evenson & Gollin, 2003; Ligon & Sadoulet, 2018; Otsuka & Muraoka, 2017).

Overall, given that sorghum is a multipurpose crop (for food, feed and cash) in our study area, our results suggest that the adoption of SITs can substantially improve the grain yield and net revenues of smallholders, 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 SITs in the study area, which implies that there are considerable missing opportunities that sorghum-producing households can harness through the adoption of SITs. Rather surprising, we find that the adoption of only GAPs had a very small yield-decreasing effect of about 2% and no statistically significant effect on net revenue. This indicates that GAPs work best in conjunction with the use of ISVs. A plausible explanation for the unexpected negative effect of adopting

only GAPs relates to the responsiveness of the type of sorghum variety to GAPs. Local varieties are susceptible to diseases, drought (Yahaya & Shimelis, 2021) and the parasitic weed *Striga hermonthica* (Belay, 2018) which cannot be managed with GAPs alone. The ISVs are specifically bred to have higher yield potentials and often possess traits (such as resistance to diseases, drought and Striga and tolerance to drought) that make them more resilient to biotic and abiotic stresses. When combined with GAPs such as tailored fertilizer use, planting density, and planting time, ISVs may fully express their genetic potential and achieve higher yields. In contrast, traditional sorghum varieties that are susceptible to the biotic and abiotic stresses may not have the same response to GAP, resulting into either no change in yield or to lower yields and consequently lower revenue. The various ISVs promoted in Nigeria differ in maturity period from late (for Southern Guinea Savannah) to medium (for Northern Guinea and Sudan Savannah) and to early (for Sudano Sahel and Sahel Savannah) maturing varieties. Thus, if farmers use varieties with a late-maturing trait, a trait most traditional varieties possess in the semi-arid Sudan or Sahel savannah, the varieties will perform poorly even with GAPs, due to drought stress and photosensitivity (Akinseye et al., 2020). More empirical studies may help to clarify the unexpected negative effect of adopting only GAPs in other study areas.

5.5. Robustness check

Table 6 shows the ATT estimates using the AIPW. The adoption of only ISVs increased yield and net revenue on average, by 25% and 68%, respectively, while the adoption of both ISVs and GAPs increased sorghum yield and net revenue by 95% and 129%, respectively, which is a significant improvement compared to those plots that had adopted only ISVs. As with the MESR estimates, AIPW estimates show that the adoption of only GAPs resulted in a negative effect on yield and net revenues. However, we observe some differences in effect sizes between the ATT estimates using MESR and AIPW, which is likely because MESR controls for potential selection bias arising from both observable and unobserved factors while AIPW controls for only observable factors. Abdoulaye et al. (2018) also reported a similar divergence in effect size between a model that accounts for both observable and unobserved heterogeneity and a model that

Table 6. Robustness checks using AIPW.

Outcomes		Adoption decision		ATT	% Gain
		To adopt ($j = 2,3,4$)	Not to adopt ($j = 1$)		
Sorghum yield	ISV_0GAP_1	1135.02	1493.08	−358.06***	−23.98
			(11.89)	(24.80)	
	ISV_1GAP_0	1794.43	1430.86	363.57***	25.41
			(10.89)	(36.66)	
	ISV_1GAP_1	2334.28s	1195.76	1138.52***	95.21
			(8.27)	(17.34)	
Sorghum net revenue	ISV_0GAP_1	39946.86	60339.97	−20393.11***	−33.80
			(1526.28)	(803.85)	
	ISV_1GAP_0	94349.03	56288.45	38060.58***	67.62
			(722.69)	(3935.80)	
	ISV_1GAP_1	103193.99	45029.28	58164.71***	129.17
			(1608.01)	(676.65)	

Notes: Standard errors reported in parentheses, *** denote significance at 1% level

accounts for only observable heterogeneity. In general, the estimates in Table 6 using the AIPW approach are qualitatively consistent with those obtained using the MESR approach.

6. Conclusions

Using a large household survey data from a sample of 1680 households and 3310 plots in the sorghum belt of Nigeria, we measure the impact of sustainable intensification technologies adoption on yield and net revenue of smallholder sorghum farmers. We estimate the impact of sustainable intensification technologies using the multinomial endogenous switching regression, which accounts for potential selection bias from observed and unobserved heterogeneity. Our findings show that a larger share of the sorghum plots was cultivated without ISVs and/or GAPs. This suggests that despite the increasing investment in sorghum varietal improvement and agronomic management research and the resulting varietal turnover, it does not translate into widespread adoption of the SITs. Among other factors, household size, years of spousal education, awareness of SITs and extension contact strongly explains the adoption of SITs in the study area, as they all had a positive and significant influence on all categories of adopters. This suggests that better access to varietal information about SITs and better access to education would help to increase the adoption of SITs. Thus, policymakers and development partners should increase investments in SIT dissemination to allow better access to information on the availability of the seeds, the varietal traits, the agronomic 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 the reach of smallholders at a more affordable price. Our findings show that the adoption of SITs doubled sorghum yield and nearly doubled the net revenue of adopters. In light of the relatively low adoption of SITs that we find, the sorghum yield and net revenues-increasing effects of SITs adoption imply that there are considerable missing opportunities that sorghum-producing households can harness through the adoption of SITs. The policy implication of this is that increasing investments in promoting widespread adoption of SITs can boost the productivity and farm income of sorghum-producing households, which can potentially improve the food security and wellbeing of the households, given that sorghum is a multipurpose crop. This aligns with how productivity growth can contribute to realizing the twin goals of eradicating extreme poverty and hunger in SSA (Sustainable Development Goals 1 and 2).

Notes

1. Local Government Areas (LGAs) in Nigeria are the administrative units below the state and the number of LGAs differs between the states.
2. j_i represents the technology choice. $j_1 = ISV_0GAP_0$, $j_2 = ISV_0GAP_1$, $j_3 = ISV_1GAP_0$, $j_4 = ISV_1GAP_1$
3. We acknowledge that the use of extension contact as an instrument is not incontestable, especially from the point of view of exogeneity of the instrument, which often applies to most instruments in the literature, as discussed in Kubitza and Krishna (2020). However, the use of extension contact is plausible in our study setting because

access to extension is less likely to have a direct effect on sorghum yield and net revenue and can only have an indirect effect that can arise through its effect on farmers' decision to adopt agricultural technologies, such as SITs. Thus, it is reasonable to assume that extension contact can ease decision-relevant information constraints and thus, it can directly affect adoption decisions but is less likely to directly affect the outcomes of adoption decisions. In addition, the results of our falsification test show that the instrument is strongly correlated with the adoption of SITs, but not with sorghum yield and net revenue outcomes of non-adopters. Furthermore, extension-related instruments have been successfully applied in previous studies on the impacts of agricultural technologies (e.g., Abdallah et al., 2021; Kamara et al., 2022; Khonje et al., 2018; Martey et al., 2020; Mellon Bedi et al., 2022). Lastly, our robustness check using the augmented inverse probability weighting (AIPW) also allays possible concerns associated with the use of inappropriate instruments.

Data availability statement

The data used in this paper are accessible on request from the corresponding author.

Disclosure statement

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