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Research article

Estimating the distributional impact of innovation platforms on income of smallholder maize farmers in Nigeria

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ABSTRACT

This research studies the distributional effects of IP adoption on the farm income of smallholder maize farmers in Nigeria in an effort to move beyond the standard mean impact assessment of agricultural interventions. In order to account for selection bias that may result from both observed and unobserved factors, the study used a conditional instrumental variable quantile treatment effects (IV-QTE) strategy. The use of IPs greatly affects the revenue distributions of maize producers, as empirical evidence from the outcomes shows. Particularly, the impacts of adoption are stronger at the lower tails and just above the mean of the income distributions, indicating that impoverished farming households benefit more from the strategic functions of IP adoption in boosting income. These findings highlight how important it is to effectively target and disseminate improved agricultural technologies in order to increase the revenue of smallholder maize farmers in Nigeria from maize production. Agricultural research information and access to extension services are two policy tools that can help improve the successful adoption and diffusion of any agricultural intervention without favoring any particular groups.

1. Introduction

Smallholder agricultural development in developing nations faces obstacles and challenges related to persistent food insecurity, volatile food prices, and worries about food safety and sustainability, but it also has more opportunities because of rising domestic and global agricultural market demand [1–3]. These concerns, along with the fact that many regions of Africa lack adequate public funding for agricultural research and development (R&D), have compelled governments to look for alternate strategies for fostering innovation [4,5]. Because of this changing environment, the industry must constantly innovate in order to provide long-term socioeconomic growth [6,7]. As a result, the agricultural innovation systems (AIS) method has become well-known as a framework for comprehending obstacles and spotting chances to improve agricultural systems' potential for innovation, particularly in sub-Saharan Africa (SSA) [8,9].

As posited by Hagmann et al. [10], In order to increase the efficiency of the delivery of agricultural research in Africa, FARA "coined" IAR4D in 2003. IAR4D brings together a variety of social and economic actors, such as those involved in value chains, in order to I learn and act collaboratively (social learning), and (ii) integrate knowledge and networks from which innovation that is pertinent

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to the local context might emerge. IAR4D is context-specific and addresses regional issues to lessen rural poverty and enhance living conditions. IAR4D seeks to achieve these effects through IPs. Agro-food processors, traders, input dealers, financial institutions (such as microfinance and banks), policy-makers, transporters, and the media, including rural radio, all interact with research, farmers and farmer organizations, advisory services (public and private), traders, and input dealers. The IP also serves as a vehicle for change in these interactions.

Multi-stakeholder platforms may offer a useful strategy for enhancing the effect of agricultural research beyond its initial development, according to a growing body of empirical data [11,12]. In SSA, where concerns are frequently voiced about the effectiveness of these initiatives to eliminate poverty and provide value for money by enhancing the welfare of smallholder farmers, there is rising empirical evidence of the economic and welfare implications of innovation platforms (IP). Current research has revealed how IPs play a role in dairy farms, with improved maize varieties having positive effects on yield and household welfare in Africa. [13]; creating food self-reliance among smallholder farmers [14]; stimulating smallholder dairy market and livestock feed improvements through local innovation platforms [15]. Except for [16], which estimated the impact of agricultural innovation platforms on smallholder livelihoods but neglected to account for the distributional impact of IPs on the income, none of these studies, to the best of our knowledge, took into account the impact of IPs on the income of smallholder farmers. Since almost 95% of impact assessment studies have concentrated on overall mean impacts, this is not just restricted to research on the effects of improved maize varieties [17].

As a result, there is not much research to support the distributional effects of IP adoption on smallholder farmers' income in Africa. This is quite unexpected given the possibility that the outcome variable distributions could alter in a variety of ways that average analysis cannot uncover. For instance, the distribution of income disparity among farmers may rise in the upper tail while declining at the lower tail. According to the distribution of the outcome factors, which Kassie et al. [18] acknowledged may change, not all participants may gain equally from improved technology. In light of this, the goal of this study was to assess the distributional effects of IP adoption on smallholder maize farmers' revenue in the study area. In a similar vein, while generally speaking IP adoption may benefit commercial farm-holders, it may still fail to improve the income of smallholder maize farmers, who are the intended beneficiaries, particularly if there is poor targeting in dissemination. This problem was taken into account in this study by analyzing the distributional effects of IP adoption. It is crucial to identify the farmers who are vulnerable so that effective extension services and increased income can be targeted at them.

2. Research methodology

2.1. Study area, data and sampling

In the continent, the SSA CP is being implemented in three Stages. With a size of 83,900 square kilometers that spans both Nigeria and Niger, the Kano, Katsina, and Maradi (KKM) Region is home to over 18.3 million people. The Sahelian zone (Sahel), the Sudan Savanna (SS), and the Northern Guinea Savanna are the three agro ecological zones (AEZs) that cross all of West and Central Africa at this latitude, and the KKM pilot learning site is situated on the border between south central Niger and north central Nigeria (NGS). Average temperatures drop as one travels from the northern to the southern portions of this Area, while annual rainfall and the length of the growing season rise. Cereals (pearl millet, sorghum, maize, upland rice, and wheat), legumes (groundnut, cowpea, and soybeans), roots and tubers (cassava, and sweet potato), and cotton are the main crops in the PLS. Sesame and tiger nuts (Cyperus esculentus) are two further rising crops (Sesamum indicum). The majority of vegetable crops, such as watermelon, tomatoes, cabbage, and peppers, are cultivated under irrigation. Livestock is a crucial component of the production systems in each of the three agro-ecological zones.

Taskforces within the sub-Saharan African Challenge Program, which was funded by the Forum for Agricultural Research in Africa, carried out the survey that provided the data used in this study (FARA). The sample frame was drawn from several districts, and it was chosen to reflect the three main taskforces in the KKM PLS. A random sample of villages within each ward, a sample of district wards, and a random sample of homes within each selected village were used to choose a sample of households in each district. Last but not least, a household was kept in the sample if it was assumed that it belonged to one of the 180 villages chosen from the clean, conventional, or IP/action sites.

In 2010–2011, the midline survey was carried out. In total, 1800 households from 180 villages were surveyed by 3 Task Forces (TFs). They include the Sudan Savanna, the Sahel Savanna, and the Northern Guinea Savanna (NGS) (SS). IAR4D and counterfactual to select the villages where the treatment is being applied, that is, villages where IAR4D are introduced, villages/communities where conventional approaches were in operation, and villages where no interventions had been carried out over the last 2–5 years, had previously been applied and carried out in the three TFs within the previously selected districts.

2.2. Empirical estimation techniques

Households make decisions to optimize their anticipated enjoyment. The predicted costs and advantages of adopting a technology, as well as household choices that are impacted by numerous factors, determine household utility. The adoption of IPs by smallholder maize farmers was conceptualized in this study using the notion of utility satisfaction. Improved wellbeing, with an implicit rise in farmers' income, may result from the use of IPs. A risk-averse farmer maximizes utility when they adopt IPs where the benefits of adoption less the costs of adoption outweigh the advantages realized without adoption. To examine the distributional impact of adoption of IPs on the income of maize farmers, a conditional IVQTE regression framework was employed. A conditional linear quantile model was specified and presented as follows:

$$Y_i^{\tau} = X_i \varpi^{\tau} + IP_i \beta^{\tau} + \varepsilon_i \tag{1}$$

Where β^{τ} signifies the quantile treatment effect (QTE) of the adoption of innovation platforms, IP_i, on Y corresponding to the τ^{th} quantile of the distribution of the income of the farmers. X_i is a vector of observed covariates that comprises of socio-economic characteristics, farm practices and other farm-specific variables; ϖ^{τ} is a vector of parameters of the covariates to be estimated; ε_i is the unobserved random variable or error term.

Estimates of the distributional impacts of adopting IPs may be inaccurate and inconsistent due to the assumption expressed in Equation (1) that the farmer's decision to adopt IPs is exogenous. However, the parameter estimate will be skewed because farmers self-select into adopting IPs and the decision is likely endogenous [19]. However, there are unobservable factors that influence both farmers' decisions to adopt and the outcome variables, such as innate farm management abilities, which can result in estimates of and that are inconsistent and biased. The conditional IV-QTEs technique created by Ref. [20] was used to account for these estimate problems. The use of a valid binary instrumental variable that complies with the exclusion restriction requirements is required for this method; specifically, the variable must not be linked with the potential outcome through any other channel than the treatment variable. In the context of our study, a valid instrument must be connected to the farmer's choice to adopt but unconnected to the revenue of smallholder maize farmers.

It is challenging to choose the best instrument, as empirical research has suggested. In previous studies, it has been proposed, among others, by Abdoulaye et al. [21] and Shiferaw et al. [22] that access to knowledge about better agricultural technology is a good instrument for its adoption. This study makes advantage of information access from innovation platforms as a tool for IP adoption. In theory, it makes sense to contend that farmers' access to information on a certain technology can influence farmers' decisions to embrace and use IPs, though it may not always do so. Given the assumption of the existence of a valid instrument, the empirical specification of the [20] conditional IV-QTEs model is specified as follows:

$$(\wedge \Psi^{\tau}_{IV.} \wedge \Upsilon^{\tau}_{IV}) = \overset{argmin}{\Psi}, \Upsilon \sum W_i^{AAI} \times \varphi_{\tau}(Y_i - X_i \varpi - PI_i \beta) \tag{2}$$

With

$$W_i^{AAI} = 1 - \frac{PI_i(1 - Z_i)}{1 - \Pr(Z = 1/X_i)} - \frac{(1 - PI_i)Z_i}{1 - \Pr(Z = 1/X_i)} \tag{3}$$

Where Z is the instrumental variable (access to IP information). The local QTE among the compliers, or the group of farmers who have access to varietal information and have adopted IPs, is the effect that is assumed to be causative. The weights in equation (3) are not always positive by design, and the minimand is not always convex. Abadie et al. [20] acknowledge this problem and suggested an alternative positive weight $W_i^{AAI+} = E(W_i^{AAI} | Y_i, PI_i, X_i)$ that can be estimated using a non-parametric local linear regression. The probability $\Pr(Z = 1/X_i)$ of having innovation information is needed to compute the weight is estimated using a local logit non-parametric estimator, as detailed in Ref. [17].

3. Results and discussion

3.1. The descriptive statistics of the smallholder maize farmers in the study area

This section summarizes the dependent and explanatory variables that were included in the model estimations, as well as the

Table 1
The descriptive statistics of the smallholder maize farmers in the study area.

Variable	Pooled	Std.Dev.	Non-adopters			Adopters	t-value
	Mean		Mean	Std.Dev.	Mean	Std. Dev.	
IP adoption	0.87	0.33					
Log of income	7.20	1.48	7.332	1.343	6.990	1.387	2.656
Location_tskngs	0.29	0.45	0.28	0.44	0.27	0.45	0.27 NS
Access to extension	0.33	0.47	0.32	0.46	0.353	0.47	0.80 NS
Gender	0.95	0.20	0.96	0.19	0.93	0.25	1.86*
Age	48.95	8.56	48.95	8.55	48.75	8.79	0.30 NS
Education of the household head	2.92	2.71	2.95	2.72	3.01	2.90	0.26 NS
Male children between 16 and 58 years	3.43	3.90	3.46	3.87	3.30	4.45	0.496 NS
Female children between 16 and 58 years	3.25	3.57	3.22	3.27	3.06	3.12	0.64 NS
Household size	11.65	6.60	11.90	6.65	10.42	6.05	2.75***
Farming experience	30.35	14.06	30.86	14.33	27.51	12.07	−2.96***
Amount of credit received	30057.28	120,000	29250.96	126795.5	33333.94	98478.91	0.34 NS
Use of information	8.83	5.06	8.84	5.32	8.60	4.41	0.59 NS
Request for agricultural information	11	8.10	11.09	8.92	10.68	5.31	0.61 NS
Knowledge of IPs	8.87	84.33	6.90	56.73	25.03	202.275	2.59***
Food double	7.22	3.85	7.20	3.86	7.27	3.72	0.19 NS
Agricultural research	0.23	0.47	0.22	0.48	0.27	0.45	1.47 NS

descriptive and one sample *t*-test results. The log of maize production income serves as the dependent variable. This study draws its empirical details from research on the factors influencing the adoption of new technologies and innovations [23–25]. Table 1 lists the explanatory variables' descriptions and corresponding means. To account for household variability, the socioeconomic parameters of gender, age, educational level, household size, and years of maize cultivation were incorporated in the model. It has been proposed that these factors may have an impact on how smallholder maize producers embrace IPs. Around 95% of the 1180 smallholder mazer farmers were men, and 5% were women. The average age of the farmers in the sample was 49, indicating that the bulk of the farmers were in the prime of their lives. The majority of respondents (about 60%) have completed at least an elementary level of education. It is anticipated that the level of education will reflect the level of farming expertise needed to benefit from enhanced technologies, such as innovation platforms, for increased income. Credit amount, information use, information requests about agriculture, access to agricultural research, and information about innovation are other factors that are taken into account. These factors are included because it is assumed that they have an impact on IP adoption and income.

3.2. Determinants of adoption of innovation platforms among smallholder maize farmers

Table 2 displays the findings of the parameter estimates from the probit model of the factors influencing the adoption of an innovative platform. The findings demonstrate that a few household socio-economic traits, institutional factors, and geography variables are statistically important in influencing smallholder maize farmers' adoption of IPs.

The adoption of IPs and the coefficient of children in the home under the age of 16 showed a statistically significant unfavorable association. This suggests that the likelihood of adopting IPs among the offspring of the household heads reduced, which may be because younger farmers view farming as a menial task. The socioeconomic milieu of the younger farmers mostly portrays farming as a "poor man's" career marked by lengthy working hours with little financial reward and low social standing [26,27].

The adoption of IPs is greatly influenced by the age of the household head since older farmers have more experience with farm tasks and are more familiar with the production environment than younger farmers. Yet, the findings of this study indicate that children (both male and female) between the ages of 16 and 58 have a statistically significant negative sign and influence the uptake of innovation platforms in the study area. The conclusion of the result is that the likelihood of an older farmer adopting IPs decreases. This may be explained by the fact that as farmers age, they become less willing to take risks and are less inclined to accept new technologies, whereas younger farmers are more willing to do so. The study's findings support those of Ghosh-Jerath et al. [28] and Ojo and Baiyegunhi [29], who noted that younger farmers are more energetic, inventive, and willing to take chances. They also have better access to information than elderly farmers who prefer to stay with tried-and-true techniques, allowing them to use a variety of cutting-edge agricultural technologies. The findings indicate that the size of a farmer's household has a positive coefficient and is statistically significant, indicating that in the study area, the likelihood to adopt an innovation platform is determined by the size of a maize farmer's household. A larger household means a more labor-intensive unit, which increases agricultural output and influences one's propensity to participate in IPs. This is supported by the findings of Belay et al. [30], who showed that family size significantly and favorably improves the likelihood of adoption of agricultural technology. The marginal effect results in Table 3 show that a unit

Table 2
Estimates of adoption of IPs amongst maize farmers-Probit model.

IP Participation	Coef.	St. Err.	*P*-value	Margin	Std. Err.	*P*-value
Gender	0.293	0.459	0.522	0.053	0.083	0.521
Age of the household head	0.048	0.030	0.112	0.009	0.005	0.108
Education of the household head	−0.029	0.057	0.609	−0.005	0.010	0.609
Male children between 16 and 58 years	−0.170	0.068	0.012**	−0.031	0.012	0.010*
Female children between 16 and 58 years	−0.134	0.077	0.081*	−0.024	0.014	0.077*
Age below 16	−0.205	0.089	0.022**	−0.037	0.016	0.018**
Age above 59	−0.032	0.108	0.766	−0.006	0.020	0.766
Household size	0.045	0.026	0.082*	0.008	0.005	0.078*
Farming experience	0.003	0.013	0.844	0.000	0.002	0.844
Amount of credit received	0.000	0.000	0.014**	0.000	0.000	0.011**
Use of information	−0.065	0.050	0.194	−0.012	0.009	0.191
Request for agricultural information	0.089	0.041	0.030**	0.016	0.007	0.027**
Knowledge of IPs	−0.005	0.034	0.892	−0.001	0.006	0.892
Food double	−0.038	0.033	0.237	−0.007	0.006	0.234
Agricultural research	0.215	0.295	0.465	0.039	0.053	0.463
Innovation information	0.380	0.266	0.152	0.069	0.048	0.150
Location_ tskngs	−1.009	0.584	0.084*	−0.184	0.105	0.081*
Location_ Tsksahel	−0.996	0.360	0.006***	−0.181	0.064	0.005***
Constant	1.668	1.323	0.208			
Mean dependent var	0.857					
Pseudo r-squared	0.196					
Chi-square	38.240					
Akaike crit. (AIC)	196.666					
Bayesian crit. (BIC)	266.027					
Prob > chi2	0.006					

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

(one additional household member) increase in the household increases the risk of engaging in IPs by 0.08%. The household size variable also showed a significant and favorable marginal influence in the studies by Debalke [31] and Belay et al. [30], demonstrating that the larger the family size, the more likely it is that maize farmers will participate in IPs in the studied areas. The farmers may use all of the knowledge at their disposal as a cure-all for better living conditions because they have more financial and other resources at their disposal. Access to credit is a significant factor improving the uptake of innovation, claims Tizale [32]. According to the study's findings, smallholder maize farmers are more likely to participate in an innovation platform when they have access to more credit. This finding suggests that farmers are more likely to adopt innovation if they have access to agricultural loans in greater numbers. This conclusion may be explained by the fact that the majority of farmers frequently work in agriculture to raise their households' standard of living. As a result, they have easier access to funding through agricultural loans as they expand their agricultural activities and focus on agricultural innovation for better living conditions. The results are in line with those of a research by Sinyolo et al. [33], who found that access to finance increases agricultural productivity, which increases farm income and provides farmers with incentives to enhance agricultural practices. The results of this study, however, differ from those of Hossain et al. [34], who discovered that farmers with larger households have a propensity to use agricultural finance for non-farm purposes in order to support the entire household. In this study, the location variable is crucial in determining the farmers' tendency to adopt and use innovation platforms. Less likely to adopt IPs are agricultural households in the Sahel Savanna (SaS) and Sudan Savanna (SS) regions. The outcome demonstrates that the Sahel Savanna (SaS) and Sudan Savanna (SS) regions' coefficients are adverse and statistically significant. This implies the significance of geography in influencing smallholder maize producers' adoption of IPs. As a result, farmers in these areas have a lesser predisposition than others to embrace IPs. The significance of some particular locales in affecting farmers' choices of agricultural technologies has also been noted in earlier research like those by Hinkel [35] and Below et al. [36]. Having more information helps agricultural families accept new technologies and productivity inputs by increasing their awareness of these factors. It's noteworthy to see that information requests relating to agriculture are statistically significant and favorable. This finding has the conclusion that smallholder farmers are more likely to make use of innovation platforms if they have better access to agricultural information, whether through interactions with extension agents or farmers-based groups. This result validates the argument made by Archer et al. [37], who proposed that the poor agricultural performance of smallholder farmers in underdeveloped countries is due to a lack of knowledge and resources. The finding is also consistent with research by Mulwa et al. [38] and Ojo et al. [39], which discovered a positive and statistically significant impact of access to FBO, extension services, and improved agricultural technologies.

Table 4 reports the distributional effects of IP adoption on smallholder maize farmers' income based on conditional IV-QTE. The findings indicate that different quantiles of the income distribution have different percentage impacts of IP adoption. The percentage impact of adoption is found to be greater in the lower quantiles of the income distribution (Q0.25 and Q0.50), while lower estimates of the percentage impact are found in the upper quantiles (Q0.75), with the highest percentage being found just slightly above the median quantile (0.90). The results showed that IPs have substantial effects in the quantiles below and above the median (Q0.25, 0.50, and 0.75), whereas there was no statistically significant influence of adoption in the Q0.9. A normal distributional curve can be seen in the distributional impact. This shows that, in terms of percentage income growth, farming households with low and slightly above median incomes tend to significantly benefit more from the use of IPs. This is consistent with the conclusion of Frölich and Melly [17], who proposed that the quantiles had a normal distribution. This result lends even more support to the IPs project, which aims to increase the productivity of small-scale and rural farmers alike.

Table 3
Impact of IPs adoption on income of smallholder maize farmers in Nigeria.

Income	Q25		Q50		Q75		Q90	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
IP Participation	0.874	0.166***	0.988	0.574*	1.653	0.615***	0.042	1.051
Age of household head	0.037	0.013***	0.018	0.008**	−0.005	0.008	−0.011	0.011
Education level household head	0.058	0.047	0.010	0.039	0.028	0.034	0.015	0.045
Male Aged 16to58	−0.171	0.089*	−0.120	0.112	−0.044	0.093	0.050	0.074
Female Aged 16to58	−0.092	0.071	−0.050	0.085	0.062	0.109	0.010	0.111
Household size	−0.003	0.029	0.063	0.033*	0.083	0.058	0.104	0.048**
Farming experience	0.001	0.000*	−0.000	0.000	−0.001	0.000***	−0.002	0.001***
Amount of credit	0.000	0.000***	0.000	0.000	0.000	0.000	−0.000	0.000
Use of information	0.150	0.051***	0.004	0.059	0.062	0.043	0.002	0.141
Request for agricultural information	−0.144	0.044***	−0.021	0.039	−0.114	0.050***	−0.087	0.138
Learning in IPs	0.116	0.026***	0.107	0.030***	0.028	0.025	0.009	0.022
Food double	0.103	0.053*	0.107	0.030***	0.049	0.042	0.023	0.026
Access to research information	0.906	0.261***	0.629	0.236***	0.090	0.363	0.031	0.623
Location_tskngs	−0.221	0.365	−0.534	0.364	0.651	0.303**	0.621	0.306**
Access to extension	−0.802	0.221***	−0.795	0.194***	−0.528	0.174***	−0.361	0.352
Gender	1.454	0.527***	1.604	0.248***	0.942	0.673	1.427	0.355***
Constant	0.973	0.764	2.028	0.670***	4.561	1.598***	6.884	1.300***

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4
Distributional effects of the adoption of IPs on income based on Conditional IV-QTE.

	Q0.25	Q0.5	Q0.75	Q0.9
Treatment effect of adoption	0.874	0.988	1.653	0.042
Standard error	0.166***	0.574*	0.615***	1.051
% impact of adoption[k]	19.04	17.51	27.05	0.6

[k] Indicates the adoption of IPs' percentage influence on each farmer's revenue quantile. The percentages were calculated by dividing the fitted data, with the adoption dummy set to zero, by the coefficient on IP adoption, and treating the remaining covariates to mean values (Abadie et al., 2002). All estimations include set of controls included in Table 2.

4. Conclusion and policy recommendations

The distributional impacts of the adoption of IPs on the income of smallholder farmers were examined using the IV-QTE approach, which controls for selectivity bias that may result from observed and unobserved features. The study specifically looks at the elements that smallholder maize farmers in Nigeria consider when deciding whether to use IPs and how adoption impacts the distribution of farm income. Additionally, this approach provides a clear picture of the diverse adoption effects that are obscured by the average adoption effects of the better technology, which are already well-documented in the literature. Access to IP information was used as an instrumental variable for accurate distributional impact analysis of IP adoption. The empirical results showed that there is significant variation in the distributional effects of IP adoption, with the implications of adoption varying dramatically along the income distributions. This finding has the implication that farming households with low incomes typically stand to gain the most from the adoption of IPs. The results of this study lend empirical support to the idea that the creation and spread of IPs can greatly increase the earnings of smallholder farmers, thus addressing their poor income. Interestingly, according to the study's findings, farmers at the bottom and slightly above the mean of the income distributions experienced significant increases in their income in proportion; however, it is crucial to keep in mind that these farmers might also be confronted with a sudden rise in costs and a lack of access to more advanced technologies. This justifies providing impoverished farmers with ongoing assistance so they can eventually benefit from agricultural technology.

Particularly, the empirical findings on the factors influencing the adoption of IPs among smallholder maize farmers showed the significance of a number of farm management, socioeconomic, and institutional factors. In SSA, where concerns are frequently voiced regarding the efficacy of these technologies to decrease poverty and offer value for money by improving farm yield, there is emerging empirical evidence of the economic and welfare consequences of adoption of enhanced agricultural technologies. Therefore, it is recommended that future research take into account the distributional effects of IPs on a number of welfare outcomes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Appendix

Acronyms	Full meaning
IPs	Innovation platforms
IV-QTE	Instrumental variable quantile treatment effects
R&D	Research and development
SSA CP	Sub-Saharan Africa a Challenge Programme
FARA	Forum for Agricultural Research in Africa
IAR4D	Integrated agricultural research for development
KKM PLS	*Kano-Katsina-Maradi Pilot Learning Site (KKM PLS)*
AEZs	Agro-Ecological Zones
NGS	The Northern Guinea Savanna
(SaS)	Sahel Savanna
(SS)	Sudan Savanna

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