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The Impact of Genetically Modified Cowpea on Yields, Postharvest Losses, and Profitability in Nigeria

Findings from a Cluster Randomized Controlled Trial

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Notices

Abstract

We assess the impacts of a genetically modified pod borer-resistant (PBR) cowpea variety in Nigeria through a cluster randomized controlled trial conducted in two major cowpea-cultivating states. Our design allows us to examine the impacts of PBR cowpea with and without a package of complementary inputs (fertilizer and insecticides) and in comparison to farmers who received only a conventional improved cowpea variety. Results indicate that farmers who received and planted PBR cowpea experienced significant increases in yield (21 percent) and net margins (49 percent) compared to those growing the conventional variety, with larger gains observed among those provided with the inputs package. Analysis of heterogeneous effects indicates substantial variation in outcomes based on baseline characteristics such as household size, landholding, pest control practices, and wealth. Estimation of group average treatment effects and classification analysis using a causal machine learning approach identify plot size, pesticide use, and assets as key drivers of impact heterogeneity. Findings highlight the need for targeted dissemination strategies to realize the sizable benefits of PBR cowpea for small-scale, resource-constrained farmers.

Keywords: Genetically modified cowpea, PBR cowpea, cluster randomized controlled trial, machine learning, Nigeria

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1. Introduction

Technological advancement is a critical means of enhancing agricultural productivity and improving food and nutrition security in many low- and middle-income countries (Suri and Udry, 2022; Emerick et al., 2016; Dercon and Christiaensen, 2011). However, in many countries in sub-Saharan Africa (SSA), this advancement has been slow, despite the urgent need for technical solutions to address adverse weather events and climate change, pest and disease pressures, degraded soils, and other factors that contribute to low rates of productivity (Wollburg et al., 2024; Fisher et al., 2015; Kassie et al., 2015; Ragasa et al., 2025). These challenges are exacerbated by high input costs, credit and informational constraints, labor supply constraints, and a range of behavioral constraints, all of which suggest heterogeneous and uncertain returns to the adoption of new technologies by farmers (Macours, 2019; Suri, 2011; Amare et al., 2024).

Across SSA, policymakers and development agencies recognize the sustained adoption of improved crop varieties as an important pathway toward accelerating agricultural productivity growth (AGRA, 2025; AfDB, 2016). Leguminous crops are widely acknowledged as playing an important role in this pathway as sources of food and fodder, as an income-generating crop for smallholders, as a means of enhancing soil fertility, and as a cost-effective source of protein, minerals, and essential amino acids for human nutrition (Gonçalves et al., 2016; Phillip et al., 2019). Among Africa's grain legumes, cowpea (*Vigna unguiculata*) occupies the largest cultivated area, with West Africa, particularly Nigeria and Niger, accounting for more than 75 percent of the continent's total production area (NAERLS, 2021). Nigeria also stands as the world's leading consumer of cowpea at approximately 3.6 million tons annually, a figure that includes both national production and imports from neighboring countries such as Niger, Cameroon, and Burkina Faso. At the household level, cowpea's significance is evident in consumption habits: around 52 percent of Africa's total production is consumed domestically, underscoring its vital role in household diets (Nkomo et al., 2021; Manda et al., 2019). Cowpea is a key dietary staple in northern Nigeria. Surveys indicate that about 35 percent of households consume cowpea three times a week, 23 percent more frequently, 30 percent twice weekly, and only 12 percent once a week or less, reaffirming its role in household diets and food security (Manda et al., 2020).

Smallholder farmers across SSA cultivate most of the region's cowpea but often realize low yields and profit that are attributable to various production challenges. Both biotic and abiotic stress limit productivity, with insect infestations posing the most serious threat (Bett et al., 2017; Kormawa et al., 2000, 2002). Cowpea is highly susceptible to different pest attacks throughout all stages of cultivation and storage (Nwagboso et al., 2024; Bawa et al., 2017). Among these, the legume pod borer (LPB; *Maruca vitrata*) is particularly destructive, capable of reducing yields by up to 80 percent in affected regions, and in severe cases, leading to total crop failure if not effectively managed (Boukar et al., 2018; Reddy et al., 2017; Bett et al., 2017). LPB larvae feed on buds and flowers, bore into pods, and destroy developing seeds. While several methods exist to control pest infestations, including the application of insecticides to the standing crop at various stages of growth, these tend to be costly and can be harmful to humans and the environment. Given the crop's importance and the significance of these threats to its production, reducing susceptibility to LBP damage and increasing yields is an R&D priority in many SSA countries. This is particularly the case for Nigeria, where cowpea improvement is at the forefront of the country's research and policy agendas (Adegbaju et al., 2024) and receives attention in Nigeria's National Agricultural Technology and Innovation Policy (NATIP) (2022–2027) (FMARD, 2022).

In 2019, Nigeria's Nigerian National Varietal Release Committee approved for variety registration and commercial release a GM cowpea variety known as SAMPEA 20-T (see NSPI 2025a for details on SAMPLEA 20-T's pedigree and characteristics). Developed through a collaborative research program involving both Nigerian scientists and international partners, the variety incorporates genetic traits that confer resistance to LPB. It is also the first GM food staple crop released in Nigeria and only the second GM food staple crop released in SSA (Andam et al., 2024a,b; Mockshell et al., 2024; Akinbo et al., 2021; Addae et al., 2020).

We examine the impact of this new PBR cowpea variety with an encouragement design and a clustered randomized controlled trial (c-RCT) conducted in two major cowpea-cultivating states of Nigeria. Our study provides the first causal evidence on farmers' experiences with this technology and its associated agronomic traits in Nigeria. Our study offers novel empirical evidence by investigating the impact of a single trait in a single crop in SSA, with the aim of bringing rigor to the evaluation of GM crops' impacts under farmers' conditions and encouraging early replication studies for other traits, crops, and countries in SSA.[1] Our trial estimates the impact of PBR cowpea on yields, postharvest losses, and profits at the farm-household level during a single growing season in 2023, following a pre-analysis plan set forth in Andam et al. (2024).

Participating farmers were randomly assigned to one of three study arms in which they were provided: (1) PBR cowpea seed with complementary inputs, specifically fertilizer and insecticides, and training; (2) PBR cowpea seed and training only; or (3) conventional cowpea seed and training only. The encouragement aspect of the trial's design—the provision of free seed, inputs, and training—was introduced to address the very nascent stage of PBR cowpea awareness and adoption among farmers in Nigeria and the study area. Specifically, the encouragement was meant to incentivize uptake at levels and rates required to detect the effects of the intervention which, in its absence, might be far too low due to farmers' unfamiliarity with the new variety and technology and their related unwillingness to try it.

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[1] Of particular interest is the recent introduction of drought-tolerant, insect-resistant GM maize in Nigeria and Ethiopia and PBR cowpea in Ghana (ISAAA, 2024, 2025).

This experimental design enables us to causally identify and quantify both the overall and relative impacts of PBR cowpea across multiple outcomes. It also facilitates the analysis of heterogeneous effects among subgroups within our sample. Identifying these overall, relative, and differential impacts is essential for developing efficient, cost-effective, and scalable strategies to promote adoption of PBR cowpea and realize its associated benefits. Our approach is a next step in the evaluation of PBR cowpea in that it builds on confined field trials and farmer-managed trials conducted by scientists involved in the international collaboration to develop the technology. Our study brings this research into farmers' own fields and subjects the technology to farmers' own real-world conditions to ensure both agroecological validity and practical relevance.

Results show that adoption of PBR cowpea increases yields by about 20 percent and net margins by nearly 46 percent, with larger gains realized by farmers who receive complementary inputs. To account for heterogeneity in effects, we apply causal machine learning (CML) methods and find that treatment effects are consistently positive across ecologically distinct regions, though heterogeneous across farmer types. Variation in impact is strongly associated with differences in plot size, pesticide use, and household assets, suggesting that resource constraints shape farmers' ability to benefit from technology. Overall, our findings provide robust experimental evidence that PBR cowpea substantially improves productivity and profitability, with important implications for the scaling and targeting of GM crops in SSA.

This study makes several contributions to the literature. First, unlike the majority of prior studies that evaluate the impact of GM crops, we provide experimentally derived causal estimates rather than relying on estimates from quasi-experimental methods applied to observational data (Klümper and Qaim, 2014; Smale et al., 2009). The only study to employ an experimental approach to an exploration of GM crop impacts is Ahmed et al. (2021), which reports positive effects of *Bt* eggplant cultivation in Bangladesh across a number of outcomes. We draw several elements from this study in the experimental design described below.[2]

Second, our study contributes to the literature on impact evaluation methods by integrating traditional regression analysis with machine learning techniques, specifically a Causal Forest model. While conventional regression methods such as analysis of covariance (ANCOVA) are commonly used to estimate average and heterogeneous treatment effects, they typically impose linearity and additivity assumptions that may mask complex, nonlinear interactions underlying treatment effect heterogeneity. In contrast, the Causal Forest framework provides a flexible, data-driven approach for uncovering heterogeneous effects, allowing the functional forms of relationships to emerge from the data rather than imposing them *a priori*. This dual

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[2] Following the Ahmed et al. (2021) study, Ahsanuzzaman and Zilberman (2024) explore the same question using a quasi-experimental approach—propensity score matching with cross-sectional data collected from farmers cultivating *Bt* and non-*Bt* eggplant in Bangladesh—and report similar results alongside a thoughtful discussion on the contribution of different methodological approaches to research on technology adoption and impact.

methodology strengthens internal validity by confirming results obtained through conventional methods, while enhancing external relevance by uncovering nuanced patterns that standard models may miss.

Third, unlike controlled research-station or farmer-managed trials that focus primarily on evaluating the technology itself, field-based randomized controlled trials (RCTs) capture how farmers interact with the technology within their social and economic environments. These types of evaluations provide the kind of empirical evidence that directly informs public debate and policy decisions. Relatedly, the study demonstrates the value of evaluating new technologies under real-world farmer conditions immediately following their release; that is, before they have been widely disseminated across the target population and market. By generating early and actionable insights before technology has been extensively adopted, our study provides guidance for future delivery and scaling strategies, both of which have a significant public policy element to them. This guidance can be particularly relevant for countries that have recently approved GM food crops, such as Ghana (cowpea) and Ethiopia (maize), as well as for countries like Kenya that are still navigating the economic, social, and legal dimensions of GM crop adoption.

The remainder of this paper is structured as follows. Section 2 provides he study context, experimental design, sampling strategy, and survey design. Section 3 describes our empirical specification. Section 4 presents and discusses the results, followed by policy recommendations and conclusions in Section 5.

2. Study Context and Experimental Design

2.1. Study context

Our study was conducted in Kwara and Adamawa States, two major cowpea-producing states in Nigeria, both among the top five cowpea-producing states, with the top 50 percent of national production distributed across 10 states (National Agricultural Extension and Research Liaison Services [NAERLS], 2021). Cowpea is produced in these states under three cropping systems: intercropping (often with maize and sorghum), monocropping, and rotational cropping, with baseline survey findings indicating that intercropping is practiced by 41 percent of farmers (Andam et al., 2024b). Cowpea is cultivated for both household consumption and market sale. Our baseline survey data indicate that while 11 percent of the cowpea harvest in the prior year (2022) was self-consumed, about 42 percent of the harvest was sold to market (Andam et al., 2024b). The study was conducted during the major growing season in northern Nigeria in 2023, which extends from September through December. The 2023 season was relatively normal in terms of temperature, precipitation, and pest pressure.

2.2. Sampling strategy

The study employs a multistage sampling procedure to select states, local government areas (LGAs), communities, and farm-households for participation in the experiment, with the overall aim of providing a representative and generalizable sample. The sampling strategy is specifically designed to capture a diverse range of cowpea farming conditions and practices. The full sampling strategy is detailed in Annex A.

2.3. Experimental design

This study employs an RCT clustered at the community level. Randomization at community level allows us to capture both direct and spillover effects of technology within local production systems. The experimental design includes treatment arms with and without complementary inputs (fertilizer and insecticides), enabling evaluation of the technology's standalone and synergistic effects. Participants were adult household members who had cultivated cowpea in the previous two growing seasons in the selected states and LGAs. Communities (clusters) were randomly assigned to one of three study arms. To facilitate adoption and ensure effective implementation, the research team, in collaboration with the African Agricultural Technology Foundation (AATF) and local partners, provided targeted inputs and technical support to each group,[3] as follows.

- Treatment Group 1 (T1): 2 kilograms (kg) of PBR cowpea seed (SAMPEA 20-T) plus complementary inputs, including 15 kg of SSP fertilizer, 5 kg of NPK fertilizer, 300 milliliters (ml) of Lambda-cyhalothrin insecticide, and training.
- Treatment Group 2 (T2): 2 kg of PBR cowpea seed (SAMPEA 20-T) with training only.
- Control Group (C): 2 kg of conventional cowpea seed (SAMPEA 10) with training only.

Communities were randomly assigned to these groups to minimize selection bias and ensure that any observed effects could be attributed to the interventions rather than other characteristics. Impacts are estimated at the household, farm, and plot levels to capture both the magnitude and direction of treatment effects.

The quantities of seed provided to participating farmers in each arm were sufficient to cultivate 0.11 hectares (ha) of cowpea under recommended seeding rates, representing an average of approximately 12 percent of a household's total area allocated to cowpea at the time of the baseline survey. Farmers in the treatment arms (T1 and T2) received SAMPEA 20-T, while those in the control arm (C) were given SAMPEA 10, released in 2008 (see NSPI, 2025b). The two varieties are considered relatively similar in

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[3] In August 2023, the encouragement provided to T1 cost approximately 59,226 Nigerian Naira (NGN or ₦), while the encouragement provided to T2 and C cost approximately ₦13,431. T1 was more expensive due to the inclusion of multiple inputs. At the time, the exchange rate was approximately 767 NGN/USD.

that they are both early maturing, which allows for early harvesting and minimizes exposure to late-season stresses. SAMPEA 20-T provides higher yields (2.9 tons/hectare [t/ha]) compared to SAMPEA 10 (2.0 t/ha), with the difference largely attributable to LPB resistance (AATF, 2021). The quantities of fertilizer and insecticide provided to T1 were similarly calibrated to be sufficient to cultivate the quantity of cowpea seed provided in the package, and were based on standard recommendations (Nwagboso et al., 2024; Omoigui et al., 2020).

The training provided to all participating farmers in all three study arms was consistent apart from the information on managing PBR cowpea. All participating farmers received training on general agronomic practices for cowpea cultivation (for example, plant spacing, pesticide and fertilizer use and timing). Farmers in the treatment arms (T1 and T2) received information on the advantages of PBR and guidance on planting refugia to mitigate the development of LPB resistance to the PBR trait. Farmers in T2 and C were specifically trained on how to apply pesticides to manage pest pressures. Training was delivered by a team from AATF and extension officers with the Agricultural Development Programs (ADP) of Kwara and Adamawa States.

To mitigate the risk of contamination, our treatment clusters (communities) were located at a significant geographical distance from the control clusters. The assignment of study arms was implemented at the community level, with treatment clusters established in distinct communities separate from those designated for the control clusters. Furthermore, because PBR cowpea seed was not yet available in the market during the time of our study, control group farmers had little or no opportunity to purchase PBR cowpea seed themselves. Finally, because our experiment was conducted during a single season in an area where PBR cowpea had not been previously introduced, little scope existed for individual or social learning effects to influence our experimental design. As such, we defer investigation of the learning constraint to investigation in a subsequent phase of the study.

2.4. Survey design

We collected baseline data on February 1–17, 2023, and a second round of data on March 17–29, 2024.[4] The baseline survey was conducted prior to the intervention rollout, primarily to enhance statistical power through repeated observations (McKenzie, 2012). We use the baseline data for three specific purposes. First, we test for balance across the study arms as an indication that the randomization was carried out according to the study protocol. Second, we use the baseline data to capture time-invariant characteristics of the farm,

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[4] A third round of data collection was anticipated for the subsequent growing season to explore sustained adoption among participants, spillover effects to neighbors, and seed acquisition strategies via market and farmer-to-farmer channels. With three survey rounds, we would have labeled these as baseline, midline, and endline surveys. However, the third survey round has been postponed until further notice.

household, and individuals participating in the study, which then allows us to reduce measurement noise for these characteristics in our estimation process, as described in the next section. Third, the baseline data are used in a detailed descriptive analysis of the study site, context, and sample.

Both the baseline and second round survey collected information on: household composition and demographics; household assets; housing, water, and sanitation; credit access and use; plot information; cowpea seed sources, quantities, and prices; cowpea variety identification; agrochemical usage; pest infestation and related knowledge, use, and exposure to insecticides and herbicides; harvesting, production, consumption, and sale of cowpea; labor usage; shocks and challenges; health status; household food security; and agronomic practices. To enhance measurement precision, farm plots were measured using GPS-enabled digital applications. Field staff used specialized area measurement software that leveraged the GPS capabilities embedded in their mobile devices. This technology enabled accurate determination of plot boundaries by recording precise geographic coordinates at each perimeter point, resulting in more reliable area calculations compared to traditional manual methods. Cowpea harvests were measured using weighing scales, which removes error caused by self-reported yields.

2.5. Outcomes of interest

We examine four primary outcomes related to farm-level productivity and profitability. First, yield (kg/ha) is the total amount of crop harvested, before any losses or deductions are accounted for during postharvest handling, storage, and processing on the farm. Second, the postharvest damage rate (expressed as a percentage) captures the harvested crop that is lost or damaged; it is calculated by dividing the quantity lost or damaged by the total harvested quantity, then multiplying by 100. Third, gross margins (₦'000/ha) are the profits per hectare after subtracting production costs (pesticides, fertilizer, and labor) from sales revenues and are calculated as output × selling price – production costs. Finally, net margins (₦'000/ha) are the profits per hectare after subtracting the cost of harvest discarded (that is, accounting for postharvest losses).

This experimental design allows us to explore several testable hypotheses. First, we test whether farmers who received PBR cowpea (T1 and T2) realized lower damage, higher yields, and lower production costs compared to farmers who received conventional cowpea varieties (C). Second, we test whether farmers who received complementary inputs alongside PBR cowpea seed (that is, the provision of a subsidized package, or T1) realized greater benefits compared to farmers who received only PBR cowpea seed (T2). Third, we explore whether treatment effects varied by specific farmer, farm, or household characteristics (household wealth; farming capabilities; and gender of the plot manager).

For the first and second hypotheses, our predictions for average treatment effects are that $T1 > T2 > C$ for yield and profit outcomes. For our exploration of heterogeneous effects, we predict the following.

- Wealth heterogeneity. Poorer farmers are expected to respond significantly more to T1 than to T2, due to tighter input cost constraints. In contrast, wealthier farmers may achieve comparable gains under T2.
- Capabilities heterogeneity. Farmers with stronger baseline experience with spraying and spacing, for example, are expected to experience larger effects under T2, where input use is self-financed.
- Gender and age. Woman-managed plots or younger farmers may realize smaller gains under T2 but benefit from the additional support provided in T1.

3. Empirical Specification

3.1. ANCOVA estimation of treatment effects

We estimate treatment effects using an ANCOVA regression specification for the agricultural yield, postharvest losses, and profitability outcomes described above. The specification takes the form:

$$Y_{hc}^{R2} = \alpha_h + \alpha_1 T1_{hc} + \alpha_2 T2_{hc} + \alpha_3 X_{hc}^{R1} + \mu_{hc} \tag{1}$$

where Y_{hc}^{R2} denotes outcomes for farmer h in cluster c, measured at the second round of data collection. $T1_{hc}$ and $T2_{hc}$ are indicator variables for T1 and T2 treatments, with the control group serving as the reference category; coefficients α_1 and α_2 capture the respective treatment effects. The vector X_{hc}^{R1} comprises baseline household characteristics, including initial yield, postharvest losses, and profitability corresponding to each outcome variable. These controls account for pretreatment differences across households and enhance the precision of the estimated treatment effects, consistent with best practices in randomized evaluation analysis. Key covariates include age of the household head, gender of the plot manager, household size, household assets, and plot size. The assets variable is a composite index derived from principal component analysis (PCA), which combines information from various physical and farm assets into a single numerical value. These PCA-derived scores are standardized values that represent relative wealth or asset ownership compared to others in the sample. The ANCOVA framework also enables analysis of treatment effect heterogeneity through interactions between baseline covariates and treatment indicators, increasing efficiency (McKenzie, 2012). Given that randomization occurred at the cluster level, standard errors are clustered accordingly to account for intracluster correlation. Diagnostic checks suggest low autocorrelation between baseline and endline outcomes, consistent with ANCOVA assumptions and supporting robust estimation of average and heterogeneous treatment effects (McKenzie, 2012).

3.2. Exploring treatment effect heterogeneity

We begin by examining treatment effect heterogeneity using an extended ANCOVA specification that interacts treatment indicators with key baseline characteristics such as gender, asset wealth, and prior yield levels. These interaction terms provide an initial, parametric assessment of whether program impacts differ systematically across observable subgroups.

To flexibly capture nonlinear and high-dimensional heterogeneity beyond these predefined dimensions, we then implement a Causal Forest model (Athey and Wager, 2018) to estimate *Conditional Average Treatment Effects* (CATEs). CML approaches are well suited for randomized evaluations, as they efficiently model complex treatment–covariate interactions without requiring restrictive functional form assumptions (Chernozhukov et al., 2018; Athey and Wager, 2019). The analysis focuses on farmers who received any treatment—either PBR cowpea with complementary inputs or PBR cowpea alone—pooling both experimental arms into an "Any treatment" group. Outcomes include cowpea yield, postharvest damage rate, and profits, measured in the second-round survey. Formally, the CATE for household h is:

$$\text{CATE}_h = E[Y_{hc}^{R2}(1) - Y_{hc}^{R2}(0) \mid X_{hc}^{R1}], \tag{2}$$

where $Y_{hc}^{R2}(1)$and $Y_{hc}^{R2}(0)$ denote potential outcomes under treatment and control, respectively, and X_{hc}^{R1} represents pretreatment covariates (for example, age of the household head, gender of the plot manager, household size, household assets, and plot size). The assets variable is as defined earlier. The algorithm estimates two conditional expectation functions,

$$g_1(X) = E[Y \mid T = 1, X], \text{ and } g_0(X) = E[Y \mid T = 0, X], \tag{3}$$

and computes the predicted treatment effect as $S(X) = g_1(X) - g_0(X)$. Standard errors are clustered at the community level to account for intracluster correlation.

To assess systematic heterogeneity, we compute Group Average Treatment Effects (GATEs) by dividing the sample into Kquantiles of the predicted CATE distribution $S(X)$. For each group $G_k = \{X \mid S(X) \in I_k\}$, we estimate

$$E[\tau(X) \mid G_k], k = 1, \ldots, K. \tag{4}$$

We also estimate GATEs across quantiles of baseline outcomes Y_0 using

$$Y - \hat{g}_0(X) = \sum_{k=1}^{Q} \gamma_k \left(T - \varepsilon_0(X)\right). I(Y_0 > I_k) + \epsilon \tag{5}$$

where $\hat{g}_0(X)$ is the predicted control outcome, $\varepsilon_0(X)$ the estimated propensity score, and γ_k the average treatment effect for group k.

By conditioning on rich baseline information, the Causal Forest approach provides a detailed mapping of treatment heterogeneity, improving precision and identifying subgroups most responsive to the intervention. This framework enhances policy relevance by informing targeted program design in agricultural settings where benefits are unlikely to be evenly distributed (Chernozhukov et al., 2018; Athey and Wager, 2019; Baiardi and Naghi, 2024).

4. Results and Discussion

In this section, we present the experimental results, starting with balance tests conducted at baseline and tests of mean differences in outcomes from the second-round survey. This is followed by the ANCOVA estimation results, which assess both average treatment effects and a conventional set of heterogeneous effects hypothesized to be relevant to the study site, design, and context. Only after exploring these conventional heterogenous effects through hypothesis testing do we introduce additional estimates enhanced by a CML approach. Results are presented for: (1) treated farmers who received either the PBR cowpea plus complementary inputs (T1) or the PBR cowpea only (T2) compared to those who received the conventional cowpea variety (C); (2) treated farmers who received either treatment (T1 and T2) compared to those in the control (C); and (3) treated farmers who received different treatment intensities (T1 versus T2).

4.1. Baseline balance and descriptive results

The balancing tests conducted with baseline survey data are meant to ensure that the randomization procedure created valid and comparable groups for our subsequent analysis. Here, we present the key baseline characteristics of households across the three study arms: T1, T2, and C. No statistically significant differences arise across treatment arms in key baseline characteristics such as the age of the household head, household size, plot size, number of insecticide applications, or cowpea yield, indicating that randomization effectively ensured comparability across these core variables (Table 1 and Annex Table A1).

A few baseline characteristics do exhibit statistically significant differences across groups. Where statistically significant differences are observed between variables, they are generally small in magnitude. For example, significant differences are observed in: household assets between those who received PBR cowpea only and the conventional variety ($p < 0.05$); and quantity of pesticide used ($p < 0.05$) and pesticide costs ($p < 0.10$) between farmers who received PBR cowpea with additional inputs and the conventional variety. Overall, results from our baseline balancing tests indicate that any differences in outcomes reported in our subsequent analysis can be reasonably attributed to the treatments rather than preexisting differences.

Table 1. Balancing test at baseline for key variables

Indicator	PBR cowpea + inputs (T1)	PBR cowpea only (T2)	Conventional cowpea (C)	Significant difference in mean		
	Mean (SD)	Mean (SD)	Mean (SD)	T1 vs T2	T1 vs C	T2 vs C
Age of household head	43.96 (13.02)	43.75 (14.25)	43.76 (14.14)	0.83	0.99	0.84
Household size	6.08 (3.04)	5.88 (3.32)	6.14 (3.33)	0.47	0.87	0.61
Female plot manager	0.59 (0.49)	0.59 (0.49)	0.62 (0.48)	0.81	0.60	0.43
Household asset (PCA)	0.25 (2.36)	0.03 (2.13)	-0.16 (1.99)	0.10	0.02**	0.40
Plot size (ha)	3.18 (3.63)	3.09 (3.80)	2.77 (2.69)	0.16	0.13	0.94
Quantity produced (kg)	393.64 (314.60)	385.12 (317.40)	384.76 (317.49)	0.11	0.80	0.20
Yield (kg/ha)	525.00 (1056.67)	459.05 (968.75)	374.40 (707.19)	0.34	0.23	0.70
Number of sprays	4.64 (2.79)	4.74 (3.20)	4.50 (2.68)	0.24	0.47	0.66
Insecticides quantity (liters/ha)	13.59 (94.94)	14.82 (153.47)	6.90 (58.11)	0.84	0.32	0.38
Number of days symptoms lasted	4.09 (5.99)	4.08 (4.97)	4.42 (4.94)	0.72	0.43	0.60

Note: Asterisks (*) denote significance levels at $^* p < 0.10$, $^{**} p < 0.05$, and $^{***} p < 0.01$. SD denotes standard deviation.

The analysis begins with a comparison of mean outcomes using data from the second-round survey, conducted following the intervention rollout. Table 2 reports summary statistics for productivity, postharvest loss rates, and profitability by treatment arm, providing preliminary evidence on the effects of the intervention. The results demonstrate clear productivity advantages for both treatment groups compared to the control group. Farmers in T1 realized the highest average yield at 558 kg/ha, followed by T2 at 530 kg/ha, and compared to 452 kg/ha in the control group. This translates into 23.5 percent and 17.3 percent yield gains, respectively, compared to the mean of the control group. The difference is statistically significant at the 1 percent level for T1 versus C ($p < 0.001$) and at the 5 percent level for T2 versus C ($p < 0.05$).

Table 2 reports postharvest damage rates across treatment arms, revealing that farmers in both T1 and T2 experienced lower average damage rates compared to farmers in C. Specifically, T1 farmers reported an average loss rate of 7.60 percent, and T2 farmers 11.03 percent, compared to 12.51 percent among C farmers. Gross margins for T1 average 612 ₦'000/ha with a standard deviation of 584, T2 averages 571 ₦'000/ha, and the conventional arm averages 352 ₦'000/ha. T1 outperforms the conventional arm by 260 ₦'000/ha ($p < 0.01$), and T2 outperforms it by 219 ₦'000/ha ($p < 0.01$), demonstrating significant profitability gains for both PBR treatments. Similarly, net margins are 544 ₦'000/ha for T1, 504 ₦'000/ha for T2, and 304 ₦'000/ha for C, with T1 and T2 significantly outperforming C by 240 ₦'000/ha and 200 ₦'000/ha, respectively (both $p < 0.01$). Results also indicate higher economic returns attributable to the treatment. Overall, T1 consistently delivers the best outcomes across all metrics, particularly in reducing postharvest damage, while T2 provides significant improvements over the conventional arm in yield and profitability but not in damage reduction, indicating that complementary inputs enhance the benefits of PBR cowpea.

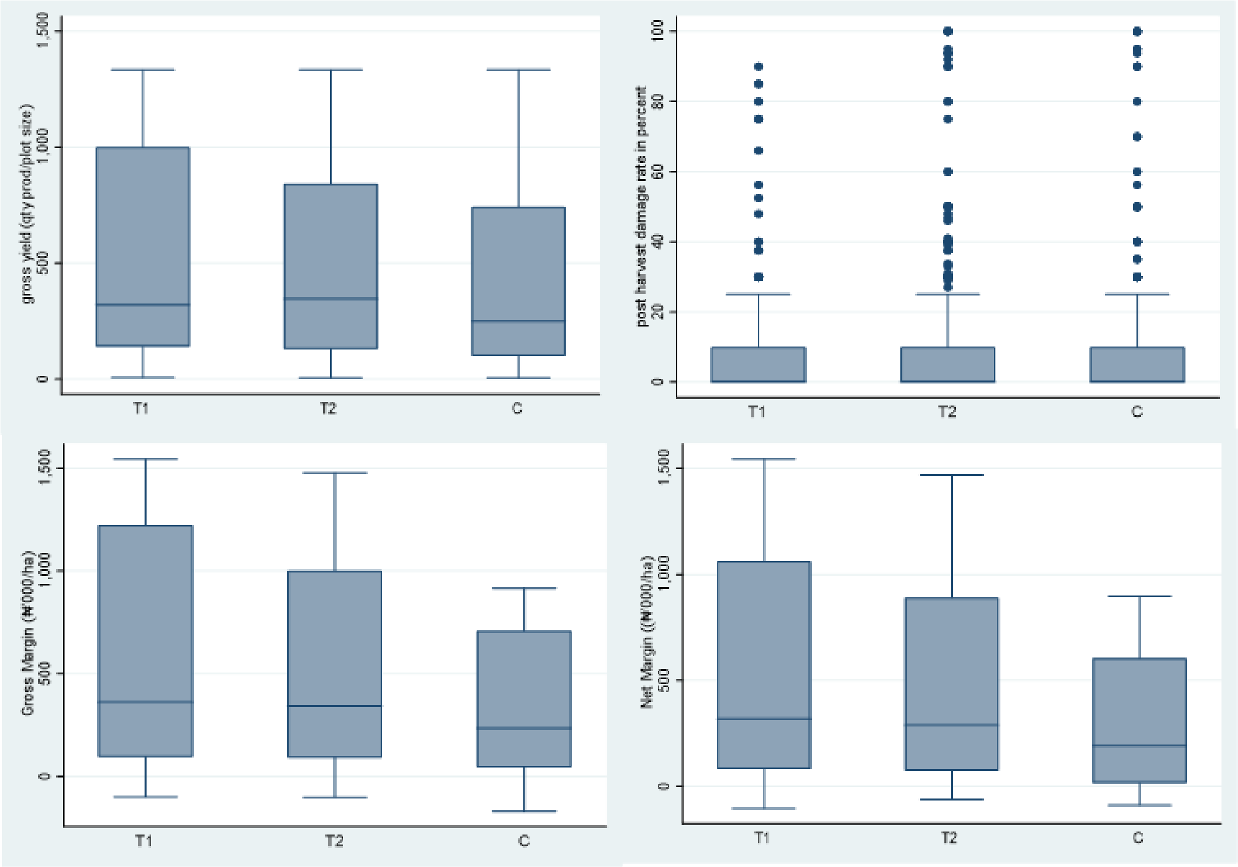
Table 2. Cowpea yield, postharvest damage, and profit comparisons at second round

Outcome variables	(T1)	(T2)	(C)	Difference in means		
	PBR cowpea+	PBR cowpea	Conventional			
	Mean (SD)	Mean (SD)	Mean (SD)	T1 vs T2	T1 vs C	T2 vs C
Yield (kg/ha)	558 (485)	530 (461)	452 (447)	0.413	0.00***	0.02**
Postharvest damage rate (%)	7.6 (14.03)	11.03 (20.22)	12.51 (22.38)	0.00^{***}	0.00^{***}	0.35
Gross margins (₦/ha ‘000)	612 (584)	571 (551)	352 (350)	0.32	0.00***	0.00***
Net margins (₦/ha ‘000)	544 (537)	504 (513)	304 (328)	0.29	0.00***	0.00***
N	333	428	306			

Note: The differences in yields, postharvest damage, and profitability are between PBR cowpea + inputs, PBR cowpea only, and conventional cowpea plots. SD denotes standard deviation. Asterisks (*) denote significance levels at $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Figure 1 illustrates these key outcomes across the three study arms. The figure highlights clear differences in outcome distributions, particularly in yield and profitability. T1 exhibits the strongest performance, showing the highest median values for both gross and net yield, as well as for gross and net margins. T2 consistently shows intermediate outcomes, while the control group records the lowest performance across all indicators. The most striking differences between treatments and controls are observed in profitability measures, where T1 farmers realize substantially higher gross and net margins.

Figure 1. Yield, postharvest damage rate, and profitability at second round



Note: The boxplots compare yield, postharvest damage rate, and profitability across the three study arms in which participating farmers were provided with: PBR cowpea, complementary inputs, and training (T1); PBR cowpea and training (T2); and conventional cowpea and training (C).

4.2. ANCOVA estimations

Next, we examine average treatment effects on yield, postharvest damage rate, and profits by employing an ANCOVA specification that includes models with and without baseline characteristics and state fixed effects (unadjusted and adjusted estimates, respectively). The latter approach improves statistical precision and accounts for potential pretreatment characteristics and imbalances across study arms.

Table 3 reports ANCOVA estimates of treatment effects on yield and postharvest damage rate. For T1, the model without controls shows a yield increase of 105.62 kg/ha ($p < 0.10$), while the model with controls estimates 100.83 kg/ha ($p < 0.10$), corresponding to a 19–20 percent improvement over the control mean of 516.18 kg/ha. For T2, the model without controls estimates a yield increase of 77.40 kg/ha (not significant), whereas the model with controls estimates 96.48 kg/ha ($p < 0.10$), indicating an 18–19 percent improvement over the control mean.

When pooling T1 and T2 as “Any treatment,” the unadjusted model indicates a yield increase of 89.75 kg/ha ($p < 0.10$), while the adjusted model shows a larger and more precisely estimated gain of 98.39 kg/ha ($p < 0.05$), corresponding to a 17–19 percent improvement in productivity. The adjusted specifications exhibit substantially higher explanatory power ($R^2 = 0.0905$ compared to 0.0076–0.0082) and statistically significant F-tests ($p < 0.01$), suggesting that the inclusion of control variables enhances model fit. Regarding postharvest damage, T1 reduces losses by 4.88 percentage points in the unadjusted model ($p < 0.05$) and 4.93 points in the adjusted model ($p < 0.05$), representing a 47 percent decline relative to the control mean of 10.39 percent. In contrast, T2 yields a smaller and statistically insignificant reduction of 1.48 percentage points in the unadjusted model and 0.84 points in the adjusted model, indicating that PBR cowpea alone does not meaningfully reduce postharvest losses. The pooled “Any treatment” category also shows an insignificant decline of 2.97 and 2.64 percentage points in the unadjusted and adjusted models, respectively. Overall, these findings highlight T1’s significant effect in mitigating postharvest damage—likely attributable to the inclusion of complementary inputs—while T2’s independent effect remains negligible.[5]

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[5] It is important to note here that the PBR-resistance trait targets LPB threats to the standing crop. LPBs are not considered a major pest at the postharvest stage.

Table 3: Estimates of treatment effects on yield (kg/ha) and postharvest damage rate (%)

	Yield				**Postharvest damage rate**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
PBR cowpea + inputs (T1)	105.615*	100.832*			-4.876**	-4.927**		
	(61.452)	(56.985)			(2.280)	(2.153)		
PBR cowpea only (T2)	77.403	96.476*			-1.483	-0.844		
	(59.491)	(54.153)			(2.491)	(2.328)		
Any treatment (T1 + T2)			89.748*	98.387**			-2.968	-2.636
			(51.618)	(47.884)			(2.190)	(2.035)
Baseline characteristics	No	Yes	No	Yes	No	Yes	No	Yes
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Constant	452.172***	268.735***	452.172***	268.432***	12.510***	8.428***	12.510***	8.713***
	(40.660)	(72.596)	(40.641)	(72.339)	(1.923)	(2.921)	(1.924)	(2.881)
Control mean	516.18	516.18	516.18	516.18	10.393	10.393	10.393	10.393
N	1,067	1,067	1,067	1,067	1,067	1,067	1,067	1,067
F-test	(2, 227)	(10, 227)	(1, 227)	(9, 227)	(2, 227)	(10, 227)	(1, 227)	(9, 227)
	1.65	5.02	3.02	5.56	2.83	3.89	1.84	3.90
Prob F	0.1952	0.000***	0.0834*	0.000***	0.061*	0.0001***	0.1768	0.0001***
R^2	0.0082	0.0905	0.0076	0.0905	0.0103	0.0669	0.0048	0.0592

Note: Figures in parentheses denote standard errors clustered at the community level. Asterisks (*) denote significance levels at * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4 reports ANCOVA estimates for gross and net margins (₦'000/ha). Columns (1) – (4) show gross margin estimates, while Columns (5) – (8) report net margins, with baseline characteristics and state fixed effects in alternating specifications. For gross margins, T1 increases profitability by 259.35 ₦'000/ha in the unadjusted model ($p < 0.01$) and 254.18 ₦'000/ha in the adjusted model ($p < 0.01$), a 49–50 percent increase over the control mean of 521.09 ₦'000/ha. T2 increases gross margins by 218.59 ₦'000/ha in the unadjusted model ($p < 0.01$) and 240.10 ₦'000/ha in the adjusted model ($p < 0.01$), a 42–46 percent increase. While yield improvements contribute directly to farm revenues, the combination of reduced pest damage and lower insecticide costs produces an even greater effect on profitability. This occurs because savings in variable input costs and reductions in crop losses enhance net returns disproportionately, resulting in a more than proportional increase in profits relative to yields.

The "Any treatment" category shows an increase of 236.43 ₦'000/ha (unadjusted, $p < 0.01$) and 246.28 ₦'000/ha (adjusted, $p < 0.01$), representing 45–47 percent gains. For net margins, T1 increases profitability by 240.43 ₦'000/ha (unadjusted, $p < 0.01$) and 235.04 ₦'000/ha (adjusted, $p < 0.01$), while T2 increases net margins by 199.94 ₦'000/ha (unadjusted, $p < 0.01$) and 216.95 ₦'000/ha (adjusted, $p < 0.01$). The pooled (Any treatment) category shows net margin increases of 217.66 ₦'000/ha (unadjusted, $p < 0.01$) and 224.89 ₦'000/ha (adjusted, $p < 0.01$). These results confirm that both T1 and T2 significantly enhance profitability, with T1 achieving the largest gains, and the effects are robust across model specifications.

Table 4: Estimates of treatment effects on gross and net margins (₦’000/ha)

	Gross margin				Net margin			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
PBR cowpea + inputs (T1)	259.354***	254.180***			240.429***	235.043***		
	(64.334)	(59.403)			(57.897)	(54.082)		
PBR cowpea only (T2)	218.585***	240.100***			199.937***	216.949***		
	(61.875)	(55.573)			(56.220)	(51.684)		
Any treatment (T1 + T2)			236.425***	246.278***			217.656***	224.889***
			(50.544)	(46.362)			(45.960)	(42.973)
Household characteristics	No	Yes	No	Yes	No	Yes	No	Yes
State fixed effect	No	Yes	No	Yes	No	Yes	No	Yes
Constant	352.47***	164.48**	352.47***	163.50**	303.67***	143.83**	303.67**	142.57**
	(32.801)	(76.131)	(32.783)	(75.961)	(30.224)	(71.257)	(30.222)	(53.125)
Control mean	521.09	521.09	521.09	521.09	458.90	458.90	458.90	458.90
N	1067	1067	1067	1067	1067	1067	1067	1067
F-test	(2, 227) 11.27	(10, 227) 7.19	(1, 227) 21.88	(9, 227) 7.96	(2, 227) 11.64	(10, 227) 6.20	(1, 227) 22.43	(9, 227) 6.93
Prob F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	352.47***	164.48**	352.47***	163.50**	303.67***	143.83**	303.67**	142.57**
	(32.80)	(76.13)	(32.78)	(75.96)	(30.24)	(71.25)	(30.22)	(53.12)
R^2	0.043	0.125	0.042	0.124	0.042	0.107	0.041	0.107

Note: Figures in parentheses denote standard errors clustered at the community level. Asterisks (*) denote significance levels at * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

4.3. ANCOVA: Heterogeneous treatment effects

We begin with augmented ANCOVA models that interact with the pooled treatment indicator ("Any treatment") with key baseline covariates along common dimensions that we hypothesize to drive heterogeneous effects. These variables are plot size, asset holdings, baseline yield, gender, and age, with the latter included to capture "experience" as a dimension of differential capabilities. These specifications include household- and community-level controls, state fixed effects, and community-clustered standard errors to improve precision and account for potential confounding variables. Table 5 presents results for the four primary outcomes: yield, postharvest damage rate, gross margins, and net margins. Each panel shows the main treatment effect, the main effect of the baseline characteristic, and the interaction between the two.

For plot size (Panel A), the treatment increases gross margins by 235.47 ₦'000/ha and net margins by 230.97 ₦'000/ha ($p < 0.01$) and reduces postharvest damage by 6.13 percentage points ($p < 0.05$) for smaller plots. For larger plots, the interaction term is significant only for postharvest damage, showing a 5.95 percentage point increase ($p < 0.05$), suggesting reduced effectiveness in damage control at larger scales. Panel B analyzes heterogeneity by asset holdings at baseline (with "Asset-rich" as a binary indicator for wealthier farmers). For asset-poor respondents (the base category), the "Any treatment" coefficient significantly raises gross margins by 182.801 ₦'000/ha ($p < 0.01$) and net margins by 157.057 ₦'000/ha ($p < 0.01$), indicating substantial profitability gains for less wealthy farmers net of controls, which intuitively makes sense as PBR cowpea provides a low-barrier technology that can level the playing field by boosting yields and reducing losses without requiring extensive upfront investments. For asset-rich respondents, the interaction term indicates additional gains of 126.19 ₦'000/ha in gross margins ($p < 0.10$) and 133.49 ₦'000/ha in net margins ($p < 0.05$), suggesting that while both groups benefit meaningfully, asset-rich farmers experience additional profitability gains. This can be explained by their greater access to complementary resources like better equipment, labor, or market connections that amplify the advantages of PBR cowpea, allowing them to scale up production or minimize risks more effectively than asset-poor farmers who, despite strong absolute gains, may be limited by fewer synergies.

For baseline yields (Panel C), the treatment increases gross margins by 176.70 ₦'000/ha and net margins by 141.96 ₦'000/ha ($p < 0.01$), with higher-yield farmers gaining an additional 97.87 ₦'000/ha (gross, $p < 0.10$) and 116.52 ₦'000/ha (net, $p < 0.10$) and a 7.44 percentage point reduction in postharvest damage ($p < 0.05$). Panel D assesses heterogeneity by gender of the plot manager. The "Any treatment" effect increases yield by 120.65 kg/ha ($p < 0.05$), gross margins by 250.98 ₦'000/ha ($p < 0.01$), and net margins by 221.66 ₦'000/ha ($p < 0.01$), indicating strong benefits across all respondents. The interaction term for woman-managed plots is not statistically significant for any outcome, suggesting that women benefit from PBR cowpea adoption at levels comparable to men, conditional on other characteristics, with no evidence of gender-based differential effects. Panel E, included to capture "experience" as a dimension of differential capabilities, examines heterogeneity by age of the household head. For all respondents, the "Any treatment" effect increases yield by 103.43 kg/ha ($p < 0.01$), gross margins by 243.41 ₦'000/ha ($p < 0.01$), and net margins by 226.39 ₦'000/ha ($p < 0.01$), demonstrating significant benefits across age groups. The interaction term for older household heads is not statistically significant for any outcome, indicating that the treatment's effects are consistent regardless of age, and that experience, as proxied by age, does not significantly alter the impact of PBR cowpea adoption.

Overall, Table 5 shows that the pooled (any treatment) category significantly improves yield, reduces postharvest damage, and increases profitability across various subgroups, but the benefits are not uniform. Farmers with larger plots, greater asset holdings, or higher baseline yields experience larger profitability gains, suggesting that PBR cowpea adoption may be scale- and skill-biased. Gender and age do not significantly influence treatment effects, indicating broad applicability of the technology across these dimensions. The consistent benefits across all respondents underscore the robustness of PBR cowpea adoption, with particular advantages for those with greater resources or capabilities.

Table 5: ANCOVA heterogenous treatment effects

	(1) Yield	**(2) Postharvest damage rate**	**(3) Gross margin**	**(4) Net margin**
Panel A: by plot size at baseline				
Any treatment (T1 + T2)	64.233	-6.129**	235.472***	230.968***
	(59.305)	(2.932)	(55.655)	(52.049)
Large plot size	-67.069	-4.163*	-33.408	-17.894
	(55.444)	(2.479)	(49.141)	(44.767)
Any treatment # Large plot size	54.520	5.953**	15.545	-13.878
	(60.766)	(2.769)	(57.599)	(52.970)
Panel B: by asset holdings at baseline				
Any treatment	58.059	-1.403	182.801***	157.057***
	(56.784)	(2.259)	(55.684)	(50.051)
Asset rich	-11.648	-0.198	-31.244	-20.885
	(61.429)	(2.955)	(51.506)	(48.498)
Any treatment # Asset-rich	79.268	-2.363	126.188*	133.491**
	(70.415)	(3.179)	(66.861)	(61.753)
Panel C: by baseline yield				
Any treatment (T1 + T2)	39.964	2.669	176.695***	141.955**
	(75.374)	(2.124)	(72.381)	(66.506)
Higher yield	-77.801	7.147***	-79.281	-101.004**
	(60.822)	(2.450)	(50.02)	(46.923)
Any treatment # Higher yield	81.957	-7.440**	97.872	116.524*
	(73.295)	(2.879)	(70.385)	(66.225)
Panel D: by gender of plot manager				
Any treatment (T1 + T2)	120.654**	-3.181	250.981***	221.655***
	(53.601)	(3.011)	(55.934)	(51.580)
Woman-managed plots	60.666	-3.144	26.364	26.788
	(56.025)	(2.722)	(46.296)	(44.137)
Any treatment # Woman-managed plots	-36.454	0.892	-7.699	5.294
	(64.347)	(3.092)	(59.742)	(55.147)
Panel E: by age of household head				
Any treatment (T1 + T2)	103.433*	-3.808	243.411***	226.391***
	(57.940)	(2.478)	(55.628)	(51.073)
Older household head	1.352	-0.905	-20.064	-22.086
	(51.241)	(2.235)	(38.847)	(35.827)
Any treatment # Older household head	-9.925	2.314	5.900	-2.652
	(61.689)	(2.717)	(57.565)	(53.406)

Note: All specifications control for baseline covariates as in the preceding tables, including farmer age, gender, input use, and other relevant preintervention characteristics. State fixed effects are included to account for regional variation. Figures in parentheses denote standard errors clustered at the community level. Asterisks (*) denote significance levels at * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

4.4. Causal Forest estimates of treatment effects

To assess heterogeneity and robustness, we estimate CATEs using a Causal Forest, which imposes no parametric structure, and evaluate systematic variation with a Best Linear Predictor (BLP) test. This approach moves beyond average treatment effects, capturing how impacts vary across the full distribution of farmer characteristics. BLP regressions reveal substantial heterogeneity (R^2: 0.314–0.633) with all F-tests highly significant ($p < 0.001$), indicating that baseline covariates meaningfully predict which households benefit most (Table 6). While the intervention has a positive average effect, effect sizes vary considerably across pretreatment characteristics.

Heterogeneity likely reflects multiple mechanisms. Gains are larger for households with greater inputs, assets, or managerial capacity and attenuated for constrained households. In some cases, severe constraints may render the intervention less effective or even counterproductive. Hence, the average treatment effect masks important variation, underscoring the need for targeted strategies and careful interpretation of mean impacts.

Table 6: Best linear predictor (BLP) test results for treatment effect heterogeneity

Outcome	BLP test R²	F-statistic	p-value	Heterogeneity detected
Yield (kg/ha)	0.314	17.87	0.000	Yes
Postharvest damage rate (%)	0.633	67.17	0.000	Yes
Gross margin (₦'000/ha)	0.443	30.96	0.000	Yes
Net margin (₦'000/ha)	0.408	26.84	0.000	Yes

Notes: The Best Linear Predictor (BLP) test was implemented following the Causal Forest estimation of Conditional Average Treatment Effects (CATEs). The predicted treatment effects (from the forest) are regressed on a set of baseline covariates in a linear model. All covariates used in the BLP test were measured at baseline, prior to the intervention, in a properly randomized controlled trial. This ensures causal identification of heterogeneity patterns. P-values: All *p*-values are from standard F-tests testing the joint significance of covariates in predicting heterogeneous effects. A p-value of 0.000 (rounded) indicates significance at $p < 0.001$.

Figure 2 presents GATE estimates with 95 percent confidence intervals across quintiles of predicted CATEs, generated from a Causal Forest model using data from an RCT. GATEs are computed for four key outcomes: gross yield, postharvest damage rate, gross margin, and net margin. This framework facilitates a deeper understanding of treatment effect heterogeneity by comparing realized outcomes across strata of predicted responsiveness. The results reveal that the intervention's impact is highly heterogeneous, both across outcomes and within CATE-based quintiles. A recurring U-shaped pattern, where the lowest (Q1) and highest (Q5) quintiles often experience the largest gains, challenges the assumption that treatment effects monotonically increase with predicted CATEs. Underperformance in mid-ranked quintiles (Q3 and Q4) suggests frictions or constraints that standard predictors fail to capture. These findings underscore the importance of combining predictive models with diagnostic tools to inform equitable and efficient targeting in biotechnology adoption.

Yield serves as the primary indicator of on-farm productivity. GATE estimates confirm substantial heterogeneity in treatment effects. Farmers in Q5 and Q4 recorded average yield gains of 154.0 kg/ha and 135.6 kg/ha, respectively, in line with moderate-to-high predicted responsiveness. Yet surprisingly, Q3 yielded only 124.1 kg/ha, and Q2 much less at 18.9 kg/ha. Notably, Q1—the group with the lowest predicted responsiveness—experienced a sizeable yield increase of 215.4 kg/ha, suggesting that traditional predictors underestimated their latent potential. These patterns indicate that agronomic potential alone does not determine yield outcomes. Q1's strong response could stem from behavioral shifts or risk-buffering, while

Q4's underperformance may reflect implementation challenges. These results emphasize the need to account for behavioral and contextual constraints in predictive targeting.

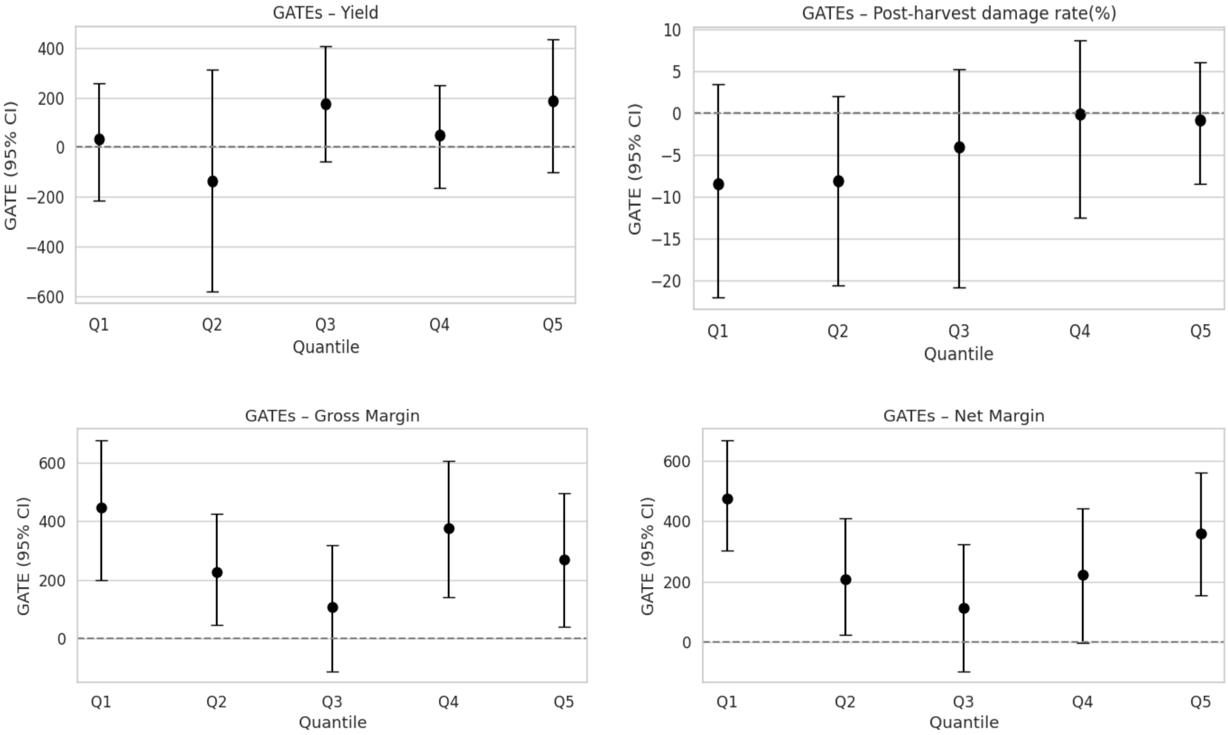
We next examine heterogeneous impacts on postharvest damage rates, which serve as an indicator of risk exposure. GATE estimates show that treatment effects are concentrated at the lower end of the predicted CATE distribution. Q1 farmers saw the largest reduction in losses (–8.4 percentage points), followed by Q2 and Q3 (–8.0 and –4.0 percentage points, respectively). In contrast, Q4 and Q5 recorded negligible effects. These results suggest that the intervention functions primarily as a risk-reduction technology, especially for asset-poor or vulnerable farmers who lack alternative postharvest solutions. For wealthier or more technically advanced farmers, the marginal value of such interventions appears limited.

GATE estimates for gross margin reveal a U-shaped pattern, with high economic gains in Q1 and Q5 (445.6 ₦'000/ha and 268.3 ₦'000/ha, respectively). Returns in Q2 and Q4 were moderate, while Q3 saw the lowest gain. This divergence between predicted and realized gains highlights how unobservable constraints—such as credit access, implementation quality, or social learning—may suppress outcomes for middle-ranked farmers. Conversely, Q1's unexpectedly high gains suggest strong returns when barriers are alleviated. These findings challenge strict CATE-based targeting and call for supportive interventions tailored to latent potential.

Net margin outcomes, which incorporate both revenues and costs, exhibit a U-shaped relationship across baseline productivity quintiles. Q1 and Q5 farmers experience the largest net returns (475.7 ₦'000/ha and 360.5 ₦'000/ha, respectively), while Q4 records the lowest (222.9 ₦'000/ha, with a wide confidence interval). This nonlinear pattern suggests heterogeneous treatment effects along the productivity distribution. Several leading theories help interpret these patterns.

First, constraint relaxation models predict that households facing severe binding constraints—such as low liquidity or limited access to inputs—benefit disproportionately when these constraints are eased, consistent with the large gains observed for Q1. Second, complementarity models suggest that households with higher baseline productivity, better market access, or greater managerial capacity can amplify returns from an intervention, which may explain the high returns for Q5. Middle-quintile farmers (Q2–Q4) appear to lack both the severe constraints that make the intervention transformative and the complementary assets that enable high returns, resulting in more moderate gains. Overall, the observed U-shaped response is consistent with theoretical predictions of heterogeneous treatment effects arising from both constraint relaxation and complementarity mechanisms. Together, the Causal Forest, BLP, and GATE analyses provide causally identified evidence of systematic heterogeneity, highlighting which subgroups benefit most and offering guidance for the equitable and efficient adoption of the intervention.

Figure 2. Group average treatment effects on yield, postharvest damage rate, and profit



Note: This figure displays Group Average Treatment Effects (GATEs) and 95% confidence intervals across quintiles of predicted Conditional Average Treatment Effects (CATEs), derived from a Causal Forest model. GATEs are calculated based on a Best Linear Predictor (BLP) regression of estimated treatment effects on baseline covariates, using experimental data from an RCT of PBR cowpea.

4.5. Explaining treatment effect heterogeneity

To complement the GATE analysis, we examine heterogeneity in treatment effects using a covariate-based classification framework. Table 7 presents regression estimates linking baseline characteristics to individual-level treatment effects for four outcomes: yield, postharvest damage, gross margin, and net margin. Each panel isolates a single outcome, highlighting the demographic, agronomic, and economic factors that shape responsiveness. This approach identifies the structural and behavioral channels through which farm-level heterogeneity influences the realized benefits of technology adoption.

Table 7: Baseline covariates driving differences in treatment effects

Covariate mean	Coefficient	p-value
Panel A: Yield (kg/ha)		
Household size	4.167	0.000
Age of household head	0.552	0.006
No. of sprays	12.209	0.000
Pest (liters/ha)	–2.225	0.000
Asset-rich	26.978	0.000
Panel B: Postharvest damage rate (%)		
Age of household head	–0.032	0.020
Plot size	0.260	0.000
No. of sprays	–0.365	0.000
Pest (liters/ha)	–0.109	0.000
Yield	–0.006	0.000
Panel C: Gross margin (₦'000/ha)		
Household size	4.195	0.000
Age of household head	1.306	0.000
No. of sprays	15.777	0.000
Pest (liters/ha)	–1.318	0.000
Asset-rich	24.168	0.000
Panel D: Net margin (₦'000/ha)		
Household size	3.317	0.003
Age of household head	0.658	0.004
No. of sprays	14.371	0.000
Pest (liters/ha)	–1.369	0.001

Notes: Coefficients from a Best Linear Predictor (BLP) regression of individual-level CATEs on baseline covariates. Negative coefficients indicate covariates associated with smaller treatment effects; positive coefficients reflect covariates associated with larger treatment effects. All covariates were measured at baseline (prior to the intervention).

Yield gains are strongly associated with household size, age, pest management practices, and asset wealth. Larger households experience higher productivity (+4.2 kg/ha per additional member, $p < 0.001$), likely reflecting greater labor availability, while older household heads achieve modestly larger gains (+0.6 kg/ha per year, p = 0.047). Baseline pest management complements the intervention: each additional spray raises yield by +12.2 kg/ha ($p < 0.001$), whereas higher pesticide volumes reduce gains (–2.2 kg/ha per liter, $p < 0.001$), suggesting diminishing returns. Asset-rich households capture substantially larger increases (+27.0 kg/ha, $p < 0.001$), highlighting the enabling role of liquidity and infrastructure. Together, these patterns indicate that both behavioral practices and resource endowments shape productivity returns, suggesting targeted support could improve outcomes for constrained but high-potential households.

Heterogeneity in postharvest losses is linked to age, plot size, pest management, and baseline yield. Older farmers reduce losses slightly (–0.03 percentage points per year, p = 0.004), potentially due to superior storage or handling knowledge. Larger plots suffer from increased damage (+0.26 percentage points/ha, $p < 0.001$), reflecting scaling challenges, while more frequent spraying (–0.37 percentage points, $p < 0.001$) and higher pesticide volumes (–0.11 percentage points, $p < 0.001$) significantly reduce spoilage. Higher baseline yield predicts smaller reductions (–0.006 kg/ha, $p < 0.001$), consistent with lower marginal improvements among more efficient farmers. These results underscore the intervention's risk-reduction role, particularly for less efficient or resource-constrained households.

Profitability outcomes mirror these patterns. Gross margin increases are larger in bigger households (+₦4.2k/ha per member, $p < 0.001$) and older households (+₦1.3k/ha per year, $p < 0.001$). Frequent baseline spraying predicts higher gains (+₦15.8k/ha, $p < 0.001$), whereas higher pesticide volumes reduce profits (–₦1.3k/ha, p = 0.006). Asset-rich farmers achieve substantially larger gross gains (+₦24.2k/ha, $p < 0.001$). Net margin effects follow similar patterns: larger households (+₦3.3k/ha per member, p = 0.002) and older heads (+₦0.7k/ha per year, p = 0.009) benefit more; frequent spraying enhances net returns (+₦14.4k/ha, $p < 0.001$); higher pesticide use reduces them (–₦1.37k/ha, p = 0.005); and higher baseline yield predicts greater net profitability (+₦0.03/ha per kg, p = 0.025). Within this rigorously designed RCT, these results show that average treatment effects conceal substantial variation across households. Responsiveness is systematically shaped by household composition, experience, agronomic practices, and asset endowments, while input inefficiencies limit gains for some farmers. Accounting for these heterogeneity patterns in targeting and adoption strategies provides actionable guidance for improving both technology uptake and welfare outcomes across diverse farm contexts.

5. Conclusions

This study provides new evidence of the impacts of a newly released GM cowpea variety in Nigeria using a c-RCT and both conventional econometric and CML methods to estimate average and heterogeneous treatment effects. We find that the introduction of PBR cowpea, both with and without complementary inputs, significantly increased yields and profitability relative to the conventional variety. Specifically, farmers who received PBR cowpea with complementary inputs (T1) experienced a 20 percent higher yield and a 46 percent higher net margin per hectare compared to control farmers. Even without the input package (T2), PBR cowpea alone yielded statistically and economically significant gains in output and profits, with yield increases of 18 percent and net margin gains of 46 percent.

We employ CML methods, specifically a Causal Forest model, to estimate heterogeneous treatment effects of the PBR cowpea intervention across two ecologically and institutionally distinct Nigerian states: Adamawa and Kwara. These regions differ markedly in agroecological conditions, rainfall patterns, and farming systems, offering a useful setting for exploring the potential external validity of the intervention. The results indicate that average treatment effects are positive and statistically significant in both states, suggesting that the intervention is effective across contrasting contexts. However, the CML estimates also reveal substantial heterogeneity in responsiveness, consistent with expectations in smallholder agricultural systems, where resource constraints and environmental variability are pervasive. These patterns underscore the importance of moving beyond average effects to understand the conditions under which interventions are most (or least) effective, an important consideration for assessing their suitability for broader rollout.

Importantly, the GATE results provide a nuanced lens through which to interpret heterogeneity in technology adoption. Across outcomes, the intervention yields the greatest returns at both extremes of predicted responsiveness, while middle-tier households often underperform. These patterns imply that ex-ante CATE models, while useful, may miss key behavioral or contextual constraints that influence outcomes, and emphasize the need for in-depth investigation of heterogeneous effects.

Several critical policy implications emerge from these findings. First, given the heterogeneity in treatment effects, there may be good reasons to explore targeting instruments that provide PBR cowpea to less-well-endowed farmers if equity considerations are important to policy decision-making. While the design of a specific targeting instrument based on, for example, the GATE analysis is beyond the scope of this study, there are clearly opportunities for deeper investigation. Integration of GATE analysis into policy design can help balance efficiency with equity, ensuring that interventions reach both high-potential and underserved farmers. As shown above, the covariate-based classification analysis reveals consistent and interpretable sources of heterogeneity across outcomes. As such, variables such as household size, farmer age, pesticide management, and asset ownership strongly predict treatment responsiveness.

Second, complementary inputs seem to amplify the gains to PBR cowpea by addressing basic resource constraints among participating farmers. This finding speaks to the continued challenge of incomplete input markets, credit markets, and other inefficiencies that influence smallholders’ productivity and profitability. Again, integration of GATE analysis into the policy design process could help remedy these issues by improving targeting strategies.

In terms of its broader policy relevance, our study contributes new and timely evidence to the ongoing debates around GM crops in Africa. Our results highlight the potential benefits of PBR cowpea for improving smallholder livelihoods and support continued investment in scaling this technology. The results presented here can help steer those debates toward more science-driven discussions on policy, regulatory, and investment options as and when similar technological innovations emerge. These innovations include drought-tolerant, insect-resistant maize, which has been approved for commercial use in Nigeria and Ethiopia, PBR cowpea in Ghana, and any number of innovations emerging from public investments in precision genetics. While results from this study of PBR cowpea are not immediately transferable to other crop-trait combinations, the rigorous approach to evaluating impact immediately following commercial release is a transferable strategy that can inform future policy, regulatory, and investment choices.

Finally, it is worth highlighting the need for continued research on the delivery and scaling of PBR cowpea in Nigeria. While this study advances the research on PBR cowpea from confined field trials and farmer-managed trials to more realistic farmer conditions, it still relies on an experimental design that encourages adoption in order to measure outcomes. This design does not allow for the study of uptake and sustained adoption over time, a point that is highlighted by both Occelli et al. (2025) and Ahsanuzzaman and Zilberman (2024) in their study of *Bt* eggplant in Bangladesh. In fact, Occelli et al. (2025) demonstrate that the promotion of *Bt* eggplant in the experimental setting featured in Ahmed et al. (2021) did not translate into sustained adoption or realized benefits five years after the intervention. Rather, their study finds evidence of widescale disadoption and no evidence of any sustained impact among treated farmers for the full range of outcomes that were originally studied. These conclusions are an important reminder that research on innovative delivery strategies for PBR cowpea—strategies that address multiple constraints to adoption, including information, financial, market, and behavioral constraints—will be critical to its sustained success at scale beyond the experiment described here.

References

AATF (African Agricultural Technology Foundation), 2021. Pod borer resistant cowpea: Why is PBR Cowpea important. FAQs. All you need to know. AATF, Nairobi. https://www.aatf-africa.org/wp-content/uploads/2021/02/PBR-Cowpea-Project-FAQ.pdf

Addae, P.C., Ishiyaku, M.F., Tignegre, J.B., Ba, M.N., Bationo, J.B., Atokple, I.D., Abudulai, M., Dabiré-Binso, C.L., Traore, F., Saba, M., & Umar, M.L., 2020. Efficacy of a cry1Ab gene for control of Maruca vitrata (Lepidoptera: Crambidae) in cowpea (Fabales: Fabaceae). *Journal of Economic Entomology*, 113(2): 974-979.

Adegbaju, M.S., Ajose, T., Adegbaju, I.E., Omosebi, T., Ajenifujah-Solebo, S.O., Falana, O.Y., Shittu, O.B., Adetunji, C.O. & Akinbo, O., 2024. Genetic engineering and genome editing technologies as catalyst for Africa's food security: the case of plant biotechnology in Nigeria. *Frontiers in Genome Editing*, 6: 1398813.

AfDB (African Development Bank), 2016. *Feed Africa: Strategy for Agricultural Transformation in Africa 2016–2025*. African Development Bank Group, Abidjan, Côte d'Ivoire

AGRA (Alliance for a Green Revolution in Africa), 2025. *Drivers of Change and Innovation.* Nairobi: AGRA.

Ahmed, A., Hoddinott, J.F., Abedin, & Hossain, N., 2021. The impacts of GM foods: Results from a randomized controlled trial of Bt eggplant in Bangladesh. *American Journal of Agricultural Economics*, 1034: 1186–1206.

Ahsanuzzaman, H.H., & Zilberman, D., 2024. Complementarity of field studies and RCTs: Evidence from *Bt* eggplant in Bangladesh, *European Review of Agricultural Economics*, 51(2): 221–247.

Ajeigbe, H. A., & Singh, B. B., 2006. Integrated pest management in cowpea: Effect of time and frequency of insecticide application on productivity. *Crop Protection*, 25(9): 920–925.

Akinbo, O., Obukosia, S., Ouedraogo, J., Sinebo, W., Savadogo, M., Timpo, S., Mbabazi, R., Maredia, K., Makinde, D. & Ambali, A., 2021. Commercial release of genetically modified crops in Africa: interface between biosafety regulatory systems and varietal release systems. *Frontiers in Plant Science*, 12: 605937.

Alene, A.D., & Manyong, V.M., 2007. Gains from high-yielding varieties with and without complementary technologies: The case of improved cowpea in Northern Nigeria. *Journal of Agricultural and Food Economics*, 21: 1–14.

Amare, M., Zavale, H., & Smart, J., 2024. Agribusiness innovation, value chain interventions, farmer input use, agricultural productivity, land access and asset ownership. *European Review of Agricultural Economics*, 51(4): 1168–1200.

Andam, K., Chambers, J., Zambrano, P., Amare, M., Spielman, D.J., Bamiwuye, T., Falck-Zepeda, J., Mockshell, J., Edeh, H., Ritter, T., Fasoranti, A., & Nwagboso, C. 2024a. *Impact Evaluation of the Use of Pod-Borer Resistant Cowpea in Nigeria*. AEA RCT Registry. February 16. https://doi.org/10.1257/rct.10474-2.0

Andam, K.S., Amare, M., Zambrano, P., Bamiwuye, T., Nwagboso, C., Fasoranti, A., Edeh, H. & Chambers, J., 2024b. *Impact Evaluation of the Use of PBR Cowpea in Nigeria: Baseline Report*. Abuja/Washington, DC: IFPRI.

Athey, S. & Wager, S., 2019. Estimating treatment effects with causal forests: An application. *Observational Studies*, 5(2): 37–51.

Azadi, H., Samiee, A., Mahmoudi, H., Jouzi, Z., Rafiaani Khachak, P., De Maeyer, P., & Witlox, F., 2016. Genetically modified crops and small-scale farmers: main opportunities and challenges. *Critical reviews in biotechnology,* 36(3): 434–446.

Ba, M.N., Huesing, J.E., Tamò, M., Higgins, T.J., Pittendrigh, B.R. & Murdock, L.L., 2018. An assessment of the risk of Bt-cowpea to non-target organisms in West Africa. *Journal of Pest Science,* 91(4): 1165–1179.

Baiardi, A. & Naghi, A.A., 2024. The value added of machine learning to causal inference: Evidence from revisited studies. *The Econometrics Journal*, 27(2): 213 –234.

Bawa, S.A., Ofori, E.K.S., & Osae, M., 2017. Species diversity and relative abundance of Callosobruchus Coleoptera: Chrysomelidae in stored cowpea in four major agricultural produce markets in the central region, Ghana. *Journal of Stored Products Research*, 72 : 117–120.

Bett, B., Gollasch, S., Moore, A., James, W., Armstrong, J., Walsh, T., Harding, R., & Higgins, T.J., 2017. Transgenic cowpeas Vigna unguiculata L. Walp expressing Bacillus thuringiensis Vip 3Ba protein are protected against the Maruca pod borer Maruca Vitrata. *Plant Cell, Tissue and Organ Culture*, 131: 335–345.

Chernozhukov, V., Demirer, M., Duflo, E. & Fernandez-Val, I., 2018. *Generic Machine Learning Inference on Heterogeneous Treatment Effects in Randomized Experiments, with an Application to Immunization in India.* Working Paper no. w24678. Cambridge, MA: National Bureau of Economic Research.

Coe, R.I.C., Njoloma, J. & Sinclair, F., 2019. To control or not to control: how do we learn more about how agronomic innovations perform on farms? *Experimental Agriculture*, *55*(S1): 303–309.

Damba, O.T., Ansah, I.G.K., Donkoh, S.A., Alhassan, A., Mullins, G.R., Yussif, K., Taylor, M.S., Tetteh, B.K. & Appiah-Twumasi, M., 2020. Effects of technology dissemination approaches on agricultural technology uptake and utilization in Northern Ghana. *Technology in Society*, 62: 101294.

Deaton, A., & Cartwright, N., 2018. Understanding and misunderstanding randomized controlled trials. *Social Science Medicine*, 210: 2–21.

Dercon, S., & Christiaensen, L. 2011. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics,* 96(2): 159–173.

Emerick, K., de Janvry, A., Sadoulet, E., & Dar, M.H. 2016. Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6): 1537–1561.

Feder, G., Just, R.E. and Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2): 255–298.

Fisher, M., Abate, T., Lunduka, R.W., Asnake, W., Alemayehu, Y. & Madulu, R.B., 2015. Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Climatic Change*, 133(2): 283 –299.

FMARD (Nigeria Federal Ministry of Agriculture and Rural Development), 2022. *National Agricultural Technology and Innovation Policy (NATI*P), 2022–2027. Abuja: FMARD.

Gonçalves, A., Goufo, P., Barros, A., Domínguez-Perles, R., Trindade, H., Rosa, E.A., Ferreira, L., Rodrigues, M., 2016. Cowpea Vigna unguiculata L. Walp, a renewed multipurpose crop for a more sustainable agri-food system: Nutritional advantages and constraints. *Journal of the Science of Food and Agriculture*, 969: 2941–2951.

Hanna, R., Mullainathan, S. and Schwartzstein, J., 2014. Learning through noticing: Theory and evidence from a field experiment. *The Quarterly Journal of Economics*, 129(3): 1311–1353.

Jack, B.K. 2013. *Market Inefficiencies and the Adoption of Agricultural Technologies in Developing Countries.* Agricultural Technology Adoption Initiative White Paper. Berkeley, CA: J-PAL (MIT) & CEGA (UC Berkley). https://escholarship.org/uc/item/6m25r19c

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O., 2015. Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. *Journal of Agricultural Economics*, 663: 640–659.

Klümper, W. & Qaim, M., 2014. A meta-analysis of the impacts of genetically modified crops. *PloS One*, 9(11): e111629.

Kormawa, P.M., Chianu, J.N. & Manyong, V.M., 2000. Cowpea demand and supply patterns in West Africa: the case of Nigeria. In *Proceedings of World Cowpea Conference*, 3: 4–7.

Kristjanson, P., Okike, I., Tarawali, S., Singh, B. B., & Manyong, V.M. 2005. Farmers' perceptions of benefits and factors affecting the adoption of improved dual-purpose cowpea in the dry savannas of Nigeria. *Agricultural Economics*, 32(2): 195–210.

Lybbert, T.J., & Bell, A. 2010. Stochastic benefit streams, learning, and technology diffusion: Why drought tolerance is not the new Bt. *AgBioForum*, 13(1): 13–24.

Lichtenberg, E., & Zilberman, D. 1986. The econometrics of damage control: Why specification matters. *American Journal of Agricultural Economics*, 68(2): 261–273.

Macours, K., 2019. Farmers' demand and the traits and diffusion of agricultural innovations in developing countries. *Annual Review of Resource Economics*, 11(1): 483–499.

Manda, J., Alene, A.D., Tufa, A.H., Abdoulaye, T., Kamara, A.Y., Olufajo, O., Olufajo, O., Boukar, O. & Manyong, V.M., 2020. Adoption and ex-post impacts of improved cowpea varieties on productivity and net returns in Nigeria. *Journal of Agricultural Economics*, 711: 165–183.

Manda, J., Alene, A.D., Tufa, A.H., Abdoulaye, T., Wossen, T., Chikoye, D. & Manyong, V., 2019. The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development*, 122: 261–271.

McKenzie, D. 2012. Beyond baseline and follow-up: The case for more T in experiments. *Journal of Development Economics*, 992 : 210–221.

Mockshell, J., Asante-Addo, C., Nwagboso, C., Ritter, T., Amare, M. & Andam, K.S., 2024. *Impact Evaluation of the Use of PBR Cowpea in Nigeria: Baseline Process Evaluation Report*. Washington, DC : IFPRI.

NAERLS (National Agricultural Extension And Research Liaison Services), 2021. *Wet Season Agricultural Performance*. In Nigeria Federal Ministry of Agriculture and Rural Development (FMARD). https://naerls.gov.ng/wp-content/uploads/2022/11/Agricultural-Performance-Survey-of-2021-Wet-Season-in-Nigeria.pdf

NBS (National Bureau of Statistics, Nigeria), 2024. *Nigeria General Household Survey-Panel (Wave 5) 2023/2024. Tracking Nigerian Households to Understand Their Resilience Over Time*. A Report by the Nigerian National Bureau of Statistics. Abuja: NBS.

________________, 2019. *General Household Survey, Panel 2018-2019, Wave 4* [Dataset]. Abuja: NBS. https://doi.org/10.48529/1HGW-DQ47

NSPI (Nigerian Seed Portal Initiative), 2025a. SAMPEA 20-T (IT97KT-PBR (IAR- TC-11-07)). https://www.seedportal.org.ng/variety.php?keyword=&category=&varid=651&cropid=3&task=view

_______________, 2025b. SAMPEA-10 (IT97K-499-35). https://www.seedportal.org.ng/variety.php?keyword=SAMPEA&category=variety&varid=84&cropid=3&task=view

Nwagboso C., Andam, K.S., Amare, M., Bamiwuye, T., & Fasoranti, A., 2024. *The Economic Importance of Cowpea in Nigeria: Trends and Implications for Achieving Agri-Food System Transformation.* IFPRI Discussion Paper no. 2241. Washington, DC: IFPRI.

Occelli, M., Kumar, K., Gomez, M., Hoddinott, J. & Tufan, H.A., 2025. Technology exposure and adoption over time: Lessons from Bt Eggplant in Bangladesh. *Agricultural Economics* (available online).

Omoigui, L.O., Kamara, A.Y., Kamai, N., Ekeleme, F., & Aliyu, K.T., 2020. *Guide to Cowpea Production in Northern Nigeria*. Ibadan: International Institute of Tropical Agriculture (IITA).

Phillip, D., Nin-Pratt, A., Zambrano, P., Wood-Sichra, U., Kato, E., Komen, J., Hanson, H., Falck-Zepeda, J.B., & Chambers, J.A., 2019. *Insect-resistant Cowpea in Nigeria: an Ex-ante Economic Assessment of a Crop Improvement Initiative.* IFPRI Discussion Paper no. 1896. Washington, DC: IFPRI.

Ragasa, C., Takeshima, H., Asante, S., Amare, M., Ma, N., Olanrewaju, O., & Duchoslav, J. 2025. Maize yield responsiveness and profitability of fertilizer: New survey evidence from six African countries. *Food Policy,* 133: 102815

Reddy, S. S., Reddy, C.N., Srinivas, C., Rao, A.M., & Reddy, S.N., 2017. Studies on population dynamics of spotted pod borer Maruca Vitrata in Dolichos Bean, Lablab Purpureus L. and their relation with abiotic factors. *Journal of Pure and Applied Biosciences,* 5(4): 1232–1239.

Smale, M., Zambrano, P., Gruère, G., Falck-Zepeda, J., Matuschke, I., Horna, D., Nagarajan, L., Yerramareddy, I., & Jones, H., 2009. *Measuring the Economic Impacts of Transgenic Crops in Developing Agriculture during the First Decade: Approaches, Findings, and Future Directions.* Food Policy Review no. 10. Washington, DC: IFPRI.

Suri, T., 2011. Selection and comparative advantage in technology adoption. *Econometrica*, 79(1): 159–209.

Suri, T. & Udry, C., 2022. Agricultural technology in Africa. *Journal of Economic Perspectives,* 36(1) : 33–56.

Takahashi, K., Muraoka, R., & Otsuka, K., 2020. Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics*, 51(1): 31–45.

Walker, T., Alene, A., Ndjeunga, J., Labarta, R., Yigezu, Y., Diagne, A., Andrade, R., Andriatsitohaina, R.M., De Groote, H., Mausch, K. & Yirga, C., 2014. *Measuring the Effectiveness of Crop Improvement Research in Sub-Saharan Africa from the Perspectives of Varietal Output, Adoption, and Change: 20 Crops, 30 Countries, and 1150 Cultivars in Farmers' Fields.* Rome: Report of the Standing Panel on Impact Assessment (SPIA), CGIAR Independent Science and Partnership Council (ISPC) Secretariat.

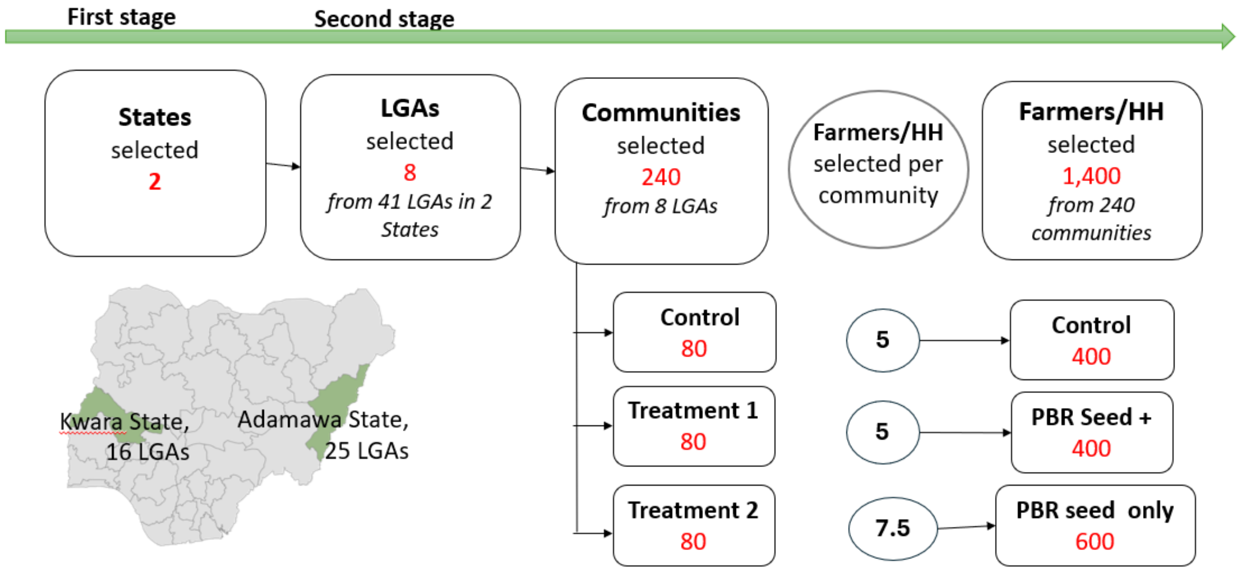
Wollburg, P., Bentze, T., Lu, Y., Udry, C., & Gollin, D. 2024. Crop yields fail to rise in smallholder farming systems in sub-Saharan Africa. *Proceedings of the National Academy of Sciences*, 121(21) : e2312519121.

Annex A: Sampling strategy

In the first stage, Adamawa and Kwara States were purposively selected from northeast and northcentral Nigeria due to their significance as major cowpea-producing states with a high share of woman-managed cowpea plots. In the second stage, four LGAs were purposively selected from each state. The selected LGAs were similar in size, socioeconomic and agroclimatic conditions, and road and market access, thus ensuring a reasonable degree of comparability. From the eight selected LGAs, 240 out of 450 communities were randomly selected based on criteria meant to ensure comparability across communities based on key contextual factors. These criteria included size, socioeconomic conditions, agroclimatic conditions, security considerations, road accessibility, and avoidance of flood-prone areas. The criteria were examined in collaboration with the Agricultural Development Program offices in both Kwara and Adamawa States. From those selected 240 communities, 160 were randomly assigned equally across the two treatment groups, and an additional 80 were randomly assigned to the control group. Within each community, households were listed, and five cowpea farmers were randomly selected from these lists to participate in the study. Figure A1 in the annex illustrates this multistage sampling procedure.

Power calculations based on data from the 2018/19 Nigeria Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) (NBS, 2019) indicated that a total sample size of approximately 1,200 farm-households was needed to detect a statistically significant increase in cowpea yields per hectare of 20 percent between the treatment and control groups, with an 80 percent chance of correctly rejecting the null hypothesis at a 0.05 level of significance. Given the intracluster correlation of 0.10, each cluster (community) required an average of at least five participants. To account for potential attrition, the sample size was increased by 200 households, resulting in a final sample size of 1,400 households (400 households for each treatment group and 600 for the control group). However, an attrition rate of 11 percent between survey rounds reduced the sample analyzed to 1,067 farmers, reflecting a loss from the original 1,200 target rather than the full 1,400. This attrition was attributed to multiple factors, including: insecurity in some LGAs across both states that prevented farmers from accessing their farms; some farmers not planting the distributed seeds—choosing instead to preserve them for future use, sell, or give them away; and additional losses due to untraceable respondents, distrust in the variety (with some waiting to observe outcomes on others' farms), and reported deaths among participants.

Figure A1. Multistage sampling procedure



Annex B. Additional balancing tests and validation of randomization procedure

Table B1. Randomization validity of baseline covariates

Indicators	PBR cowpea + inputs (T1) Mean (SD)	PBR cowpea only (T2) Mean (SD)	Conventional cowpea (C) Mean (SD)	Significant difference in mean T1 vs T2	T1 vs C	T2 vs C
Age of household head	43.96 (13.02)	43.75 (14.25)	43.76 (14.14)	0.83	0.99	0.84
Household size	6.08 (3.04)	5.88 (3.32)	6.14 (3.33)	0.47	0.87	0.61
Female plot manager	0.59 (0.49)	0.59 (0.49)	0.62 (0.48)	0.81	0.60	0.43
Household asset	0.25 (2.36)	0.03 (2.13)	-0.16 (1.99)	0.10	0.02**	0.40
Household head no education	0.23 (0.42)	0.23 (0.42)	0.27 (0.44)	0.75	0.37	0.21
Household head primary education	0.19 (0.39)	0.18 (0.39)	0.14 (0.35)	0.42	0.09*	0.31
Household head secondary education	0.33 (0.47)	0.33 (0.47)	0.32 (0.47)	0.44	0.84	0.33
Household head tertiary education	0.25 (0.43)	0.25 (0.43)	0.27 (0.44)	0.85	0.42	0.50
Household head ever married	0.94 (0.24)	0.91 (0.28)	0.92 (0.27)	0.12	0.22	0.82
Household head farm income	0.99 (0.08)	0.99 (0.07)	0.99 (0.06)	0.80	0.61	0.77
Household's primary source of light – torch/skewer	0.43 (0.49)	0.52 (0.50)	0.54 (0.50)	0.00***	0.03**	0.44
Household - improved state of house condition	0.52 (0.50)	0.45 (0.50)	0.46 (0.50)	0.14	0.18	0.99
Household - improved the outer walls of the dwelling	0.95 (0.22)	0.92 (0.26)	0.93 (0.25)	0.02**	0.19	0.35
Household - improved the roof of the main dwelling	0.95 (0.22)	0.96 (0.20)	0.94 (0.24)	0.96	0.54	0.49
Household - improved floor of the main dwelling	0.98 (0.13)	0.99 (0.10)	0.99 (0.10)	0.47	0.38	0.81
Household - improved source of cooking fuel	0.05 (0.21)	0.03 (0.17)	0.02 (0.13)	0.06*	0.69	0.15
Plot size (ha)	3.18 (3.63)	3.09 (3.80)	2.77 (2.69)	0.16	0.13	0.94
Quantity produced (kg)	393.64 (314.60)	385.12 (317.40)	384.76 (317.49)	0.11	0.80	0.20
Yield (kg/ha)	525.00 (1056.67)	459.05 (968.75)	374.40 (707.19)	0.34	0.23	0.70
Household use cultivable/arable land	0.85 (0.34)	0.85 (0.34)	0.86 (0.34)	0.31	0.77	0.50
Household soil type - sandy loam	0.30 (0.43)	0.30 (0.44)	0.34 (0.45)	0.48	0.17	0.49
Household plot source - inherited plot	0.67 (0.45)	0.72 (0.43)	0.70 (0.43)	0.35	0.80	0.52
Plot yearly rent (₦'000)	38.57 (52.73)	36.27 (40.58)	43.15 (59.74)	0.76	0.83	0.58
Practice of intercropping	0.37 (0.45)	0.36 (0.45)	0.40 (0.46)	0.59	0.37	0.66
Number of sprays	4.64 (2.79)	4.74 (3.20)	4.50 (2.68)	0.24	0.47	0.66
Insecticides quantity (liters)	6.77 (7.51)	6.50 (7.58)	6.31 (7.45)	0.15	0.53	0.46

Indicators	**PBR cowpea + inputs (T1) Mean (SD)**	**PBR cowpea only (T2) Mean (SD)**	**Conventional cowpea (C) Mean (SD)**	**Significant difference in mean**		
				T1 vs T2	**T1 vs C**	**T2 vs C**
Insecticides quantity (liters/ha)	13.59 (94.94)	14.82 (153.47)	6.90 (58.11)	0.84	0.32	0.38
Pesticide cost (₦'000/ha)	18.30 (23.55)	19.93 (25.90)	17.61 (26.90)	0.92	0.95	0.98
Herbicide use	0.83 (0.37)	0.77 (0.42)	0.81 (0.39)	0.09	0.64	0.25
Herbicide cost (₦'000/ha)	18.56 (30.10)	16.79 (27.11)	17.47 (29.35)	0.75	0.56	0.75
Quantity discarded (kg)	76.91 (147.60)	66.37 (154.06)	67.09 (115.84)	0.64	0.65	0.97
Health-related symptoms						
Headache	0.27 (0.41)	0.26 (0.40)	0.26 (0.41)	0.63	0.73	0.92
Dizziness	0.04 (0.16)	0.03 (0.15)	0.04 (0.17)	0.92	0.99	0.92
Nausea	0.01 (0.08)	0.02 (0.11)	0.01 (0.11)	0.90	0.87	0.77
Diarrhea	0.02 (0.10)	0.01 (0.07)	0.01 (0.09)	0.43	0.49	0.97
Fever	0.24 (0.38)	0.25 (0.38)	0.32 (0.41)	0.34	0.05*	0.23
Convulsion	0.004 (0.06)	0.01 (0.07)	0.001 (0.02)	0.67	0.37	0.22
Breath	0.03 (0.14)	0.06 (0.21)	0.03 (0.15)	0.39	0.74	0.23
Skin disease	0.02 (0.12)	0.04 (0.19)	0.04 (0.20)	0.48	0.16	0.44
Joint pain	0.20 (0.35)	0.22 (0.38)	0.21 (0.37)	0.51	0.42	0.84
None	0.48 (0.46)	0.47 (0.46)	0.42 (0.45)	0.62	0.18	0.35
Number of days symptoms lasted	4.09 (5.99)	4.08 (4.97)	4.42 (4.94)	0.72	0.43	0.60
Number of days symptoms prevent work	3.01 (4.96)	3.25 (4.40)	3.35 (3.09)	0.18	0.37	0.58
Total cash expenses incurred (₦'000)	4.04 (8.93)	4.15 (1.67)	4.07 (1.86)	0.88	0.97	0.51

Note: Asterisks (*) denote significance levels at * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

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