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Insecticide Use, Farmers' Self-reported Health Status, and Genetically Modified Cowpea in Nigeria

Findings from a Clustered Randomized Controlled Trial with Causal Machine Learning

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Abstract

Excessive insecticide use in smallholder agriculture can threaten human health and the environment. We evaluate the effects of receiving a genetically modified cowpea variety that confers resistance to the legume pod borer (*Maruca vitrata*) using a clustered randomized controlled trial with an encouragement design in Nigeria. We find that farmers who received the pod borer-resistant (PBR) cowpea with complementary inputs significantly reduce insecticide volumes and report fewer days of insecticide-related illness compared to farmers who only received a conventional cowpea variety. Farmers receiving PBR cowpea alone experience smaller, mostly insignificant reductions. To explore heterogeneous responses, we combine ANCOVA (analysis of covariance) interactions with machine learning-based Causal Forest estimates of Conditional Average Treatment Effects (CATEs). Results reveal that smaller, less wealthy, and labor-constrained households experience the largest reductions in insecticide use and health improvements, whereas wealthier farmers or those with higher baseline spraying practices experience lower reductions. Women-managed plots exhibit modestly higher responsiveness. Our findings highlight the importance of moving beyond average effects and seed distribution toward targeted, context-specific interventions that account for behavioral and resource constraints in smallholder farming systems.

Keywords: Genetically modified crops, PBR cowpea, insecticide use, health outcomes, cluster randomized controlled trial, machine learning, smallholder farmers, Nigeria

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Insecticide Use, Farmers' Self-reported Health Status, and Genetically Modified Cowpea in Nigeria: Findings from a Clustered Randomized Controlled Trial with Causal Machine Learning

1. Introduction

Improved crop varieties, modern inputs, and better farming practices are widely recognized as powerful levers for boosting agricultural productivity, reducing pressure on land and water resources, and enhancing climate resilience in sub-Saharan Africa's smallholder farming systems (Amare et al., 2024; Hansen and Wingender, 2023; Suri and Udry, 2022). These improvements are especially critical as Africa's population continues to grow and urbanize, intensifying food demand and land competition (Jayne et al., 2018, Amare et al., 2023). However, despite decades of investment in agricultural research and extension, the adoption of productivity-enhancing technologies among smallholders remains stubbornly low due to financial, biophysical, behavioral, and institutional constraints (Sheahan and Barrett, 2017; Hatzenbuehler et al., 2023).

Genetically modified (GM) food staple crops represent a promising pathway to productivity improvements and a more sustainable agricultural transformation in the region. GM crops allow for the introduction of valuable traits into a crop's genetic makeup to confer resilience to pests, diseases, and abiotic stresses; to reduce dependence on chemical inputs like pesticides; or to provide other agronomic or nutritional benefits (Shafiwu et al., 2022; Brookes, 2022). However, in some cases the higher yields achieved as a result of new traits may also increase the demand for inputs, labor, and management, depending on pest pressure and agronomic practices (Rani et al., 2021).

Among the traits introduced through genetic modification, resistance to lepidopteran pests conferred by genes from the soil bacterium *Bacillus thuringiensis* (*Bt*) is a particularly cost-effective and scalable option for reducing insecticide use and its associated harms among cotton, maize, soybean, and eggplant farmers in several low- and middle-income countries (LMICs) (Ahmed et al., 2021; Abedullah, et al., 2014; Areal et al., 2013; Smale et al., 2009). In late 2019, Nigeria became the first African country after South Africa to approve the commercial release of a GM food crop: the cowpea variety SAMPEA 20-T, which contains the Cry1Ab (*Bt*) gene targeting the legume pod borer *Maruca vitrata*, a major cowpea pest. Field trial data suggest this pod borer-resistant (PBR) variety has the potential to increase yields by over 20 percent and reduce insecticide use from an average of six to eight applications to just two applications during the growing season (AATF, 2024). PBR cowpea is also expected to generate economic, environmental, and health benefits to farmers, especially Women-headed households, which tend to invest more than their male counterparts in cowpea production (Andam et al., 2024a).

This study is the first to directly estimate the effects of PBR cowpea on insecticide use and health outcomes under real-world conditions for smallholder farmers and extends the analysis of PBR cowpea's effects on yields and profits first reported in Amare et al. (2025). This evidence is particularly salient given the high rates of insecticide use in Nigeria and the longstanding European ban on Nigerian cowpea imports due to high pesticide residues (NBS and World Bank, 2024; Nwagboso et al., 2024; Michelson et al., 2023). Our study evaluates the impact of receiving PBR cowpea on insecticide use and human health using data from a clustered randomized controlled trial (c-RCT) conducted in Adamawa and Kwara States of Nigeria, following a pre-analysis plan described in Andam et al. (2024b). The trial employed a randomized encouragement design with three arms, in which farmers received PBR cowpea seed either with or without complementary inputs, or conventional cowpea seed as a control. We estimate average treatment effects (ATEs) using an ANCOVA (analysis of covariance) framework and examine heterogeneous treatment effects (HTEs) through Causal Forest machine learning techniques, allowing us to identify how responsiveness varies across farm- and household-level characteristics.

This study makes three key contributions. First, we provide the first experimental evidence on the impacts of a GM crop in Africa based on self-reported insecticide use and health symptoms associated with insecticide use. Second, we advance the literature on sustainable pest management among low-income smallholder farmers by linking a genetic innovation (PBR cowpea) to insecticide use, exposure, and potential health risks. Third, we demonstrate the value of combining RCTs with machine learning methods to identify distributional effects and refine policy targeting. Our results show that farmers who received PBR cowpea with complementary inputs significantly reduce insecticide use and report fewer days of insecticide-related illness compared to farmers who only received a conventional cowpea variety. Farmers receiving PBR cowpea without the complementary inputs see smaller, mostly insignificant reductions.

Our results also show that farmers who are younger, poorer, and more labor-constrained experience the most significant benefits. In contrast, high-asset farmers are less responsive, despite often being predicted as high-yield gainers. These findings indicate that while the average effects of PBR cowpea in Nigeria are significant and positive in terms of our indicators, considerable heterogeneity among farmers exists, suggesting that a combination of experimental and predictive methods can improve the targeting of future efforts to deliver and promote the technology at scale.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and provides a broader study context, highlighting key gaps this work aims to address. Section 3 details the experimental design, including the sampling strategy, intervention components, and data collection methods. Section 4 outlines the empirical specification used to estimate treatment effects and test the study's main hypotheses. Section 5 presents descriptive results, while Section 6 reports the main empirical findings, including both ATEs and HTEs, along with a discussion of their implications. Section 7 concludes by summarizing the paper's key contributions and offering policy recommendations to enhance program effectiveness and scalability.

2. Prior Research and Study Context

A broad body of research links the overuse and misuse of chemical insecticides in smallholder agriculture to high production costs and negative human and environmental externalities (Afshari et al., 2021; Sheahan et al., 2017; Damalas and Eleftherohorinos, 2011; Huang et al., 2005; Pingali et al., 1994). These chemical compounds can be persistent and bioaccumulate in food systems, posing acute and chronic health risks to applicators and rural populations, particularly children and pregnant women (Roberts et al., 2012; Rasoul et al., 2008; UNEP, 2004). Resource-poor farmers and day laborers are more likely to spray insecticides without proper protective gear, training, or dosage control, which exacerbates exposure risks and limits productivity gains (Sharifzadeh et al., 2019; Sheahan et al., 2017; Wang et al., 2017).

Alternative approaches to pest control, such as integrated pest management (IPM) and integrated weed management, combine biological, cultural, and chemical tools to reduce reliance on insecticides while preserving yields (Norton et al., 2019). Precision agriculture technologies such as drones and field sensors have been shown to reduce off-target exposure, but their knowledge and capital intensity limit feasibility for smallholders (Taseer and Han, 2024; Emery et al., 2021). In contrast, genetic innovations, particularly GM crops, provide an embedded and scalable alternative. GM crops expressing Cry genes have shown consistent benefits in Latin America and South and Southeast Asia, particularly in cotton, maize, and soybean (Abedullah et al., 2015; Klümper and Qaim, 2014; Areal et al., 2013) and eggplant (Ahmed et al., 202; Occelli et al., 2025). These crops reduce pest pressure, lower insecticide use, and have the potential to improve health outcomes.

Notably, Ahmed et al. (2021) document a 37.5 percent reduction in pesticide costs and a significant drop in health symptoms among *Bt* eggplant farmers in Bangladesh, with similar findings reported by Ahsanuzzaman and Zilberman (2024). Kouser et al. (2019a) likewise find reduced illness and medical expenses associated with *Bt* cotton adoption in Pakistan, using a cost-of-illness framework. Pray et al. (2002) show that adoption of *Bt* cotton in China substantially reduced insecticide applications and, in turn, markedly lowered pesticide poisoning incidents among farmers. In the first two years, non-*Bt* cotton users reported poisoning rates of 22–29 percent, whereas farmers planting exclusively *Bt* varieties experienced rates of only 5–8 percent. An earlier study by Huang et al. (2005) documents the benefits of insect-resistant *Bt* rice in China, including increased yields and lower pesticide use, and demonstrates, with ample and rigorous evidence, the positive effects on farmers' health. However, except for studies in South Africa (Gouse et al., 2005), most of this literature focuses on nonstaple crops outside Africa or lacks experimental rigor. Only Ahmed et al. (2021) provides causal evidence from a well-identified experimental study design, while others rely on second-best strategies and provide limited examination of heterogeneity in impacts.

In our specific study context, insecticide use and cost are issues of particular importance. The 2023/24 General Household Survey (NBS and World Bank, 2024) revealed that 28.1 percent of cowpea farmers report insecticide use, the highest rate across major crops. This usage shows a significant gender disparity, with men-managed plots reporting twice the rate of Women-managed plots (34 percent versus 17 percent). The Government of Nigeria has identified excessive pesticide use as a national concern, prompting bans on specific products and formulations, public campaigns against injudicious use, and the promotion of IPM approaches (Government of Nigeria, 2021; Andam et al., 2024c). However, enforcement is weak, and access to training, personal protective equipment (PPE), and alternative technologies remains limited (Nwagboso et al., 2024).

Field trials and ex ante assessments in Nigeria indicate that PBR cowpea has the potential to generate substantial productivity and health gains (Phillip et al., 2019). Despite these potential benefits, adoption among smallholder farmers may be limited by low awareness, restricted seed availability, and social constraints (Andam et al., 2024a; Occelli et al., 2025). The 2019 commercial release of PBR cowpea in Nigeria provides a unique opportunity to evaluate the causal effects of receipt of PBR cowpea on insecticide use and farmer health under real-world conditions. Building on prior research on GM crops, this study estimates both ATEs among low-income farmers and HTEs, while also assessing strategies for the broader delivery of PBR cowpea at scale.

Our c-RCT randomly assigned farmers in Adamawa and Kwara States to one of two treatment arms that received either (i) PBR cowpea seed with training and complementary inputs, or (ii) PBR cowpea seed with training only, or (iii) a control group that received conventional cowpea seed and training. Using ANCOVA and Causal Forests models, we examine both ATEs and HTEs on insecticide use intensity, number of insecticide applications, and self-reported health symptoms. In doing so, this study provides new empirical evidence on the role of GM crops in smallholder production systems in low-income countries. We also illustrate how causal machine learning can uncover distributional patterns that inform more inclusive and effective technology targeting strategies in such systems and countries.

3. Experimental Design

3.1. Intervention and context

Our experimental design relies on the randomization of clusters defined at the community level, rather than at the individual farmer level. While randomization ensures that treatment and control groups are comparable across both observed and unobserved characteristics such as agroclimatic conditions, market access, and socioeconomic status, the cluster design minimizes the possibility of spillover effects between treatment arms and supports causal inference. Additional details on the experimental design are provided in Amare et al. (2025).

Communities within selected Local Government Areas (LGAs)[1] were randomly assigned to one of three groups. *Treatment Group* 1 (T1) received 2 kilograms (kg) of PBR cowpea seed (SAMPEA 20-T) along with a bundled package of complementary inputs, 15 kg of SSP (Single Super Phosphate) fertilizer, 5 kg of NPK 20-10-10 compound fertilizer, and 300 ml of a synthetic pyrethroid insecticide (Lambdacal). T1 participants also received training on recommended agronomic practices, including optimal land spacing and insecticide application.[2] Treatment Group

[1] Local Government Areas (LGAs) are administrative divisions within a country overseen by local governments. Their size and structure vary across countries but are typically subdivisions of a state, province, division, or territory. Nigeria has 774 LGAs.

[2] Lamdacal, as advertised in Nigeria, is a pyrethroid insecticide, which means that it works by disrupting the nervous system of insects. Pyrethroid insecticides are fast-acting and have long-lasting residual activity, meaning that they

2 (T2) received 2 kg of PBR cowpea seed but no other additional inputs, and the same training as noted above. Control Group (C) received 2 kg of a comparable but conventional cowpea seed (SAMPEA 10), training, and no additional inputs. The cost of each intervention is provided in Table 2.[3] See Amare et al. (2025) for additional details.

Table 1. Breakdown of intervention input quantities and cost[4]

Inputs	Treatment 1	Treatment 2 Cost (US$)	Control
PBR cowpea (2 kg)	13,431	13,431	-
Conventional cowpea (2 kg)	-	-	13,431
NPK fertilizer (5 kg)	9,133	-	-
SSP fertilizer (15 kg)	31,811	-	-
Insecticide (300 ml)	4,835	-	-
Total cost (US$)	59,226	13,431	13,431

We test the following hypotheses, which follow directly from the well-documented impact pathways for GM crops embodying the insect-resistant *Bt* trait (Ahmed et al., 2021; Klümper and Qaim, 2014; Smale et al., 2009). First, we hypothesize that farmers who cultivate PBR cowpea reduce their insecticide use as compared to farmers who cultivate conventional cowpea. Second, farmers who cultivate PBR cowpea experience improved health outcomes, specifically fewer symptoms associated with insecticide exposure, as compared to those farmers who cultivate conventional cowpea varieties. Third, treatment effects among farmers vary by farmer and farm characteristics such as gender of the household head, farm size, and wealth.

3.2. Sampling strategy and survey data

The study employed a multistage sampling strategy designed to ensure representation of the diverse cowpea farming systems in Nigeria. In the first stage, Adamawa and Kwara States were purposively selected due to their status as among the highest cowpea-producing states and particular notoriety for the high prevalence of Women-managed cowpea plots. In the second stage, four LGAs were purposively selected from each state based on comparability in terms of size,

continue to kill pests for several weeks after they are applied. Lambdacal is effective against a wide range of insects, including aphids, beetles, caterpillars, flies, mosquitoes, and termites.

[3] Note that the cost of PBR cowpea is the same as conventional cowpea in our study context. This is the price at which the study's implementing partner, the African Agricultural Technology Foundation, provided the seed for the study. However, it is recognized that commercial providers of PBR cowpea may, in the future, price the seed at a higher rate due to higher costs of production and safe stewardship of the trait embodied in the PBR cowpea. These cost issues are considered in a separate paper.

[4]During the intervention and distribution of inputs in August 2023, the exchange rate was 1,343.14 Naira per US dollar.

socioeconomic conditions, agroecological zones, and market access. From these eight LGAs, a total of 240 communities were randomly selected and assigned to treatment arms: 160 communities to the treatment groups (split evenly between T1 and T2) and 80 communities to the control group. For more detailed information on survey design and sampling strategies, see Amare et al. (2025).

Within each selected community, a household listing exercise was conducted. From this list, five cowpea-farming households were randomly selected for inclusion in the study. This within-cluster randomization enhances representativeness and internal validity. To determine the required sample size, power calculations were conducted using data from the Nigeria Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) 2018/19. Assuming an intracluster correlation of 0.10, the calculations indicated that a total sample of approximately 1,200 households would be needed to detect a 20 percent increase in cowpea yields (kilograms per hectare, or kg/ha) with 80 percent power at a 5 percent significance level. To account for potential attrition, the target sample size was increased by 200 households, yielding an intended sample of 1,400 farm households: 400 in each treatment group and 600 in the control group. See Andam et al. (2024a) for additional details. The final sample included a total of 1,067 farm households.

3.3. Measurement and outcomes

To minimize measurement error and improve the accuracy of our outcome measures, this study employed a combination of technology-assisted tools and structured survey instruments. Plot sizes were measured using GPS-enabled digital applications, and harvests were quantified using digital weighing scales. These approaches replace farmer self-reports, enhancing the precision and reliability of the data, particularly for input use rates and yield outcomes. The analysis focuses on two primary categories of outcome variables: (i) insecticide use practices; and (ii) health-related outcomes. These measures enable us to assess both direct agronomic changes and potential spillover effects on farmer well-being resulting from the PBR cowpea intervention.

3.3.1. Insecticide use

We measure the frequency and intensity of insecticide application during the cowpea-growing season, disaggregated into general insecticide use and insecticide use specifically for managing

Maruca vitrata, the insect targeted by the PBR cowpea variety. The indicators are: (i) the number of insecticide sprays used to control all insects (measured as a discrete count per cowpea plot per season); (ii) the volume of insecticide used to control all insects (measured as total liters of insecticide applied per hectare of cowpea cultivated); (iii) the number of insecticide sprays targeting *Maruca vitrata* (measured as a discrete count per plot per season, based on farmer identification of sprays directed at *Maruca* control); and (iv) the volume of insecticide used to target *Maruca vitrata* (measured in liters per hectare, capturing total insecticide volume specifically applied to manage *Maruca*). By analyzing sprays and volumes for all insects versus *Maruca*, the study aims to explore whether PBR cowpea affects general insecticide practices or is specific to the trait-targeted insect, as shown in prior studies of *Bt* crops (Ahmed et al., 2021; Kouser et al., 2019a, Kouser et al., 2019b).

3.3.2. Farmers' health-related outcomes

The study also captures self-reported health symptoms and labor productivity losses related to insecticide exposure. These are collected via structured interviews administered at the end of the growing season. Specific indicators are as follows. First, we capture the number of days that respondents report experiencing symptoms associated with insecticide exposure. This is measured as a discrete count of days the farmer experienced any of the following: dizziness, headaches, skin rashes, eye irritation, nausea, or difficulty breathing. Such symptoms are consistent with prior research on insecticide poisoning in smallholder contexts (Sheahan et al., 2017) Second, we capture the number of days that these symptoms were reported to have prevented the farmer from working. This is measured as a discrete count of days lost to illness symptoms that limited regular agricultural or household work. This indicator reflects the indirect economic cost of insecticide-related illness (Kouser et al., 2019a).

Several key points regarding the health-related outcome indicators are worth noting. First, although these health indicators are based on self-reports and cannot be medically verified, they remain a standard proxy in agricultural health studies in LMICs where clinical diagnostics are often unavailable (Dinham, 2003; Sheahan et al., 2017). Second, baseline health indicators were collected through self-reported symptoms and the number of days affected during the planting season (July–September 2022). While these measures provide information on short-term health status, they may not fully reflect individuals' prior health conditions or the intensity of those conditions. Consequently, estimated associations between treatment and health outcomes may be confounded by unobserved baseline health differences and subject to recall bias inherent in self-reported data. As such, these indicators offer only an approximation of potential health improvements from reduced insecticide exposure and should be interpreted with caution.

4. Estimation Strategy

4.1. ANCOVA estimation of treatment effects

To assess the causal impact of the PBR cowpea intervention on farmers' insecticide practices and health-related outcomes, we employ an ANCOVA specification. This approach is well-suited for settings with low autocorrelation between baseline and follow-up measurements, such as insecticide use practices and health symptoms (McKenzie, 2012).

$$Y_{hc}^{R2} = \alpha_h + \beta_1 T1_{hc} + \beta_2 T2_{hc} + \beta_3 X_{hc}^{R1} + \mu_{hc} \quad (1)$$

where Y_{hc}^{R2} denotes the outcome for the household h in a community (cluster) c measured at the second survey round. The outcome variables include: (i) number of insecticide sprays (discrete count) for all pests, (ii) volume of insecticide used (l/ha) for all insects, (iii) number of sprays for *Maruca*, (iv) volume of insecticide used (l/ha) for *Maruca*, and (v) health-related outcomes, including days of symptoms and days of work lost due to symptoms. $T1_{hc}$ and $T2_{hc}$ are treatment dummies for whether household h received PBR cowpea with inputs or PBR cowpea only, respectively. The control group (conventional cowpea, no inputs) serves as the reference category. X_{hc}^{R1} is a vector of round one (baseline) covariates, including lagged values of the outcome variable (when available), farm size, gender of the household head, and asset holding. μ_{hc} is an idiosyncratic error term.

This ANCOVA framework enhances efficiency and statistical power over difference-in-differences when outcome autocorrelation is low, as is typically the case for short-term insecticide use and health outcomes (McKenzie, 2012). Including lagged outcomes helps to control preexisting differences and accounts for unobserved heterogeneity across households. Given the randomization at the community level, standard errors are clustered at the community level to account for intracluster correlation.

4.2. Heterogeneous treatment effects

While ATEs provide an overall measure of intervention impact, they may obscure substantial variation across farmers. Identifying HTEs is essential for understanding differential impacts and guiding targeted interventions (Deaton and Cartwright, 2018). To explore variation in treatment responses, we complement standard ANCOVA-based heterogeneity tests with Causal Forests (Athey and Wager, 2018). The ANCOVA approach allows us to test whether treatment effects differ systematically across observable baseline characteristics using conventional interaction terms. Causal Forests extend this analysis by flexibly modeling high-dimensional and nonlinear heterogeneity. They estimate Conditional Average Treatment Effects (CATEs) for household h as:

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

where $Y_{hc}^{R2}(1)$ and $Y_{hc}^{R2}(0)$ are potential outcomes under treatment and control, and X_{hc}^{R1} is a vector of pretreatment covariates (for example, age, gender, education, farm size, baseline insecticide use). The algorithm estimates conditional expectations $g_1(X) = \mathbb{E}[Y \mid T = 1, X]$ and $g_0(X) = \mathbb{E}[Y \mid T = 0, X]$, computing the individual treatment effect as $S(X) = g_1(X) - g_0(X)$.

We construct Group Average Treatment Effects (GATEs) by partitioning households into quantiles of predicted responsiveness $S(X)$, enabling profiling of the most and least responsive types. Stratifying GATEs by baseline outcomes (for example, prior insecticide use) further reveals how treatment effects vary with historical behavior.

Finally, treatment effects are estimated as:

$$Y - \hat{g}_0(X) = \sum_{k=1}^{Q} \gamma_k \left(T - \varepsilon_0(X)\right). I(Y_0 > I_k) + \epsilon \tag{3}$$

where γ_k captures the ATE in each quantile. Combining ANCOVA-based interaction tests with Causal Forests allows us to rigorously assess HTEs, handle high-dimensional covariates, model flexible nonlinear relationships, and identify households most likely to benefit from interventions (Athey and Wager, 2019; Chernozhukov et al., 2018; Baiardi and Naghi, 2024a, 2024b).

5. Descriptive Results

5.1. Balancing tests at baseline

Table 2 presents summary statistics for key baseline characteristics across the three treatment arms: PBR cowpea plus inputs (T1), PBR cowpea only (T2), and the conventional cowpea control group (C). Variables include demographic and farm characteristics, such as age of the household head, gender of the plot manager, household size, asset index, cowpea plot size, insecticide use (measured in terms of both spray frequency and quantity), and baseline yield. For additional balance tests, see Amare et al. (2025).

Table 2: Balance test at baseline

	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
Women plot manager	0.59 (0.49)	0.59 (0.49)	0.62 (0.48)			
Household asset	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 (314)	385 (317)	385 (317)	0.11	0.80	0.20
Yield (kg/ha)	525 (1057)	459 (969)	374 (707)	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 (l)	6.77 (7.51)	6.50 (7.58)	6.31 (7.45)	0.15	0.53	0.46
Insecticides quantity (l/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
No. of days symptoms lasted	4.09 (5.99)	4.08 (4.97)	4.42 (4.94)	0.72	0.43	0.60
No. of days symptoms prevented work	3.01 (4.96)	3.25 (4.40)	3.35 (3.09)	0.18	0.37	0.58
Total cash expenses incurred (₦’000/ha)	4.04 (8.93)	4.15 (1.67)	4.07 (1.86)	0.88	0.97	0.51

Note: The differences in yield between PBR cowpea + inputs, PBR cowpea only, and conventional cowpea plots. SD denotes standard deviation. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These test results suggest a strong overall balance across experimental groups. Specifically, no statistically significant differences arise across arms in household head age, household size, plot size, number of insecticide sprays, or cowpea yield at baseline, suggesting randomization was successful in achieving comparability across these core variables. However, we do observe statistically significant differences across arms for a few characteristics. A statistically significant difference exists in the household asset index between T1 and the control ($p < 0.05$), as well as in the baseline quantity of insecticide used (l/ha) between T1 and C ($p < 0.05$). These minor imbalances are addressed in the analysis through the inclusion of relevant baseline covariates in the ANCOVA and Causal Forest specifications. Overall, the randomized assignment resulted in broadly balanced treatment groups at baseline, lending credibility to the internal validity of subsequent causal estimates.

5.2. Descriptive results

We examine the effects of receiving PBR cowpea on the intensity of insecticide use and farmer health. Table 3 presents summary statistics and differences in means for key outcomes across the three experimental arms: PBR cowpea with inputs (T1), PBR cowpea only (T2), and conventional cowpea (C). On average, T1 farmers applied 2.91 insecticide sprays per season, compared to 2.67 in T2 and 2.85 in C. The difference between T1 and T2 is statistically significant at the 5 percent level. While overall spray frequency was highest in T1, this likely reflects the provision of insecticides, which may encourage greater use of available resources. Nonetheless, the volume of insecticide applied per hectare was significantly lower in T1 (7.16 l/ha) than in either T2 (8.57 l/ha) or C (9.17 l/ha), with both differences statistically significant at the 1 percent level. This reduction is most pronounced for insecticide use targeting *Maruca vitrata*, where both T1 and T2 groups applied approximately 70 percent less insecticide than the control group ($p < 0.01$). These results are consistent with the insect-resistant properties of the PBR cowpea variety and indicate that farmers receiving PBR cowpea, particularly when bundled with complementary inputs, substantially reduce their reliance on chemical insecticides for targeted pest control.

Health outcomes mirror the observed differences in insecticide use, with T2 results largely resembling the control group, highlighting the additional value of bundled inputs in T1. Farmers receiving PBR cowpea with complementary inputs (T1) experienced fewer work-inhibiting health effects from insecticide exposure, averaging 0.23 days with illness symptoms compared to 0.37 days in C ($p < 0.05$), and 0.06 days unable to work versus 0.17 days in C ($p < 0.05$). Descriptive statistics in Table 4 further show that 7 percent of T1 farmers sought medical attention for related symptoms, compared to 11 percent of control farmers. These patterns suggest that receiving PBR cowpea along with full complementary support can reduce exposure risks, consistent with findings from Ahmed et al. (2021). We formalize the link between receipt of PBR cowpea and health outcomes in the subsequent analysis.

Table 3. Insecticide use and farmers' health indicators comparisons in survey round two

Outcome variables	(T1) PBR cowpea + inputs Mean (SD)	(T2) PBR cowpea only Mean (SD)	(C) Conventional cowpea Mean (SD)	Difference in means T1 vs. T2	T1 vs. C	T2 vs. C
Number of sprays (no.)	2.91 (1.35)	2.67 (1.80)	2.85 (1.84)	0.04**	0.65	0.17
Insecticide use (l/ha)	7.16 (6.54)	8.57 (7.40)	9.17 (7.42)	0.00***	0.00***	0.28
Number of sprays for *Maruca*	0.27 (0.67)	0.26 (0.64)	1.41 (2.10)	0.77	0.00***	0.00***
Insecticide for *Maruca* (l/ha)	0.50 (1.31)	0.54 (1.39)	1.69 (2.26)	0.68	0.00***	0.00***
Days of symptoms (no.)	0.23 (0.72)	0.35 (0.88)	0.37 (1.07)	0.04**	0.04**	0.69
Days prevented from working (no.)	0.06 (0.35)	0.11 (0.61)	0.17 (0.71)	0.18	0.01**	0.23
N	333	428	306			

Note: The differences in insecticide and health outcomes 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 *** $p < 0.01$.

6. Results and Discussion

We estimate the effects of receipt of PBR cowpea using a two-step strategy. First, we estimate ATEs using an ANCOVA specification that controls baseline outcomes and household characteristics, with standard errors clustered at the community level. This approach increases statistical power and accounts for pretreatment differences across treatment groups. Second, we examine HTEs using a combination of ANCOVA-based heterogeneity analysis and Causal Forest methods, generating CATEs, GATEs, and Best Linear Predictor (BLP) tests to formally assess effect heterogeneity.

6.1. Impact of PBR cowpea on insecticide use

Table 4 reports the impact of receiving PBR cowpea on insecticide spray frequency for all pests (columns 1–4) and volume applied (columns 5–8), both without and with controls for household characteristics and state fixed effects. Focusing on the specification controlling for household baseline characteristics and state fixed effects, receipt of PBR cowpea bundled with complementary inputs (T1) is associated with a significant reduction in insecticide volume. T1 farmers applied 2.094 l/ha less than the control group, representing a 25 percent reduction from the control mean of 8.304 l/ha ($p < 0.05$). In contrast, the T2 group (PBR cowpea only) exhibited a modest and statistically insignificant decline of 0.353 l/ha. Any treatment estimates indicate reductions of 1.117–1.212 l/ha (13–14 percent of the control mean), though these effects are not statistically significant at conventional levels. These regression results diverge from raw means: T1 volume is lower than both T2 and the control, but spray frequency is highest in T1, likely reflecting baseline differences in farmer characteristics. Regarding spray frequency, T2 aligns with the expected reduction (−0.134 sprays; not significant), whereas T1 shows a slight, statistically insignificant increase of 0.019 sprays ($p > 0.10$) after controlling for covariates. This counterintuitive pattern may reflect the bundled inputs in T1, which include additional pesticides and training, potentially encouraging farmers to utilize available resources more intensively.

Table 4: The impact of PBR cowpea on insecticide use

	Number of sprays (all pests)				Insecticide use (l/ha)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PBR cowpea + inputs (T1)	0.057	0.019			-2.009**	-2.094**		
	(0.194)	(0.170)			(0.890)	(0.839)		
PBR cowpea only (T2)	-0.187	-0.134			-0.593	-0.353		
	(0.215)	(0.190)			(0.911)	(0.830)		
Any treatment (T1+T2)			-0.080	-0.067			-1.212	-1.117
			(0.186)	(0.164)			(0.796)	(0.738)
Household characteristics	No	Yes	No	Yes	No	Yes	No	Yes
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Control mean	2.796	2.796	2.796	2.796	7.162	7.162	7.162	7.162
N	1067	1067	1067	1067	1067	1067	1067	1067

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

Table 5 isolates insecticide application targeting *Maruca vitrata*, revealing substantial and statistically significant reductions in both spray frequency and insecticide volume across treatment arms. Compared to the control mean of 0.858 l/ha, farmers in T1 (PBR cowpea + inputs) and T2 (PBR cowpea only) reduced insecticide use by 1.196 l/ha and 1.156 l/ha, respectively (both $p < 0.01$), corresponding to reductions of roughly 135–139 %. Similarly, any-treatment estimates indicate a reduction of approximately 1.145 sprays per plot ($p < 0.01$). Despite these pest-specific reductions, total spraying behavior did not uniformly decline. When controlling household characteristics and state fixed effects, T1 exhibits a small, statistically insignificant increase in overall sprays, while T2 shows a modest, non-significant reduction. This divergence from raw means, where T1 volume is lower than T2 or control, likely reflects baseline differences in farmer behavior and the additional training and inputs bundled in T1, which may encourage broader pesticide use. These results underscore that PBR cowpea effectively reduces insecticide use for *Maruca*, but total spraying patterns vary across farmers and pest management practices.

Consequently, examining heterogeneous treatment effects is critical to understanding the full impact of the intervention and designing targeted pest management strategies.

Table 5: The impact of PBR cowpea on insecticide use for *Maruca*

	Number of sprays for *Maruca*				Insecticide use (l/ha) for *Maruca*			
	(1)	(2)	(3)	(4)	5)	(6)	(7)	(8)
PBR cowpea + inputs (T1)	-1.138***	-1.145***			-1.196***	-1.194***		
	(0.201)	(0.200)			(0.217)	(0.214)		
PBR cowpea only (T2)	-1.152***	-1.145***			-1.156***	-1.148***		
	(0.199)	(0.195)			(0.211)	(0.207)		
Any treatment (T1+T2)			-1.146***	-1.145***			-1.173***	-1.168***
			(0.197)	(0.194)			(0.204)	(0.201)
Household characteristics	No	Yes	No	Yes	No	Yes	No	Yes
State fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Control mean	0.594	0.594	0.594	0.594	0.858	0.858	0.858	0.858
N	1067	1067	1067	1067	1067	1067	1067	1067

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

6.2. Impact of PBR cowpea on farmers' health

We next assess whether reductions in insecticide exposure from cultivating PBR cowpea translate into improvements in farmers' self-reported health. Table 6 presents ANCOVA estimates for two health-related outcomes: (i) the number of days with insecticide-related symptoms; and (ii) the number of days those symptoms prevented farmers from working. All specifications control for baseline household characteristics, with additional models including baseline health variables (collected during the planting season, July–September 2022) and state fixed effects.

Results indicate modest but consistent improvements in self-reported health among adopters, particularly for those in the bundled treatment group (T1). Farmers in T1 report a 0.146-day reduction in symptom duration ($p < 0.10$) and 0.110 fewer work-preventing days ($p < 0.05$) relative to the control group. In contrast, the T2 group experiences smaller, statistically insignificant reductions (−0.039 and −0.068 days, respectively). Pooled "any treatment" estimates show modest declines in both indicators (−0.080 to −0.086 days), occasionally significant at the 10 percent level.

It is important to note that these health outcomes are entirely self-reported and therefore subject to recall and reporting bias. While such measures are common in household and agricultural health surveys, they may contain nonclassical measurement error if reporting accuracy varies systematically by treatment group. Accordingly, the estimated coefficients should be interpreted as indicative associations rather than definitive causal effects. Nonetheless, the consistent direction of the results across specifications suggests that receiving PBR cowpea reduces farmers' exposure to insecticides and associated health risks.

Table 6: Impacts of PBR cowpea on farmers' self-reported health outcomes

	Days of symptoms (no.)					
	(1)	(2)	(3)	(4)	(5)	(6)
PBR cowpea + inputs (T1)	-0.146*	-0.145*	-0.133			
	(0.084)	(0.083)	(0.081)			
PBR cowpea only (T2)	-0.028	-0.039	-0.022			
	(0.088)	(0.088)	(0.085)			
Any treatment (T1+T2)				-0.080	-0.085	-0.071
				(0.079)	(0.079)	(0.076)
Household characteristics	No	Yes	Yes	No	Yes	Yes
Health characteristics	No	No	Yes	No	No	Yes
State fixed effects	No	Yes	Yes	No	Yes	Yes
Control mean	0.317	0.317	0.317	0.317	0.317	0.317
N	1067	1067	1067	1067	1067	1067
	Days prevented from working (no.)					
PBR cowpea + inputs (T1)	-0.110**	-0.109**	-0.104**			
	(0.050)	(0.049)	(0.047)			
PBR cowpea only	-0.059	-0.068	-0.063			
	(0.056)	(0.055)	(0.052)			
Any treatment				-0.081	-0.086*	-0.081
				(0.049)	(0.049)	(0.046)
Household characteristics	No	Yes	Yes	No	Yes	Yes
Health characteristics	No	No	Yes	No	No	Yes
State fixed effects	No	Yes	Yes	No	Yes	Yes
Control mean	0.109	0.109	0.109	0.109	0.109	0.109
N	1067	1067	1067	1067	1067	1067

Note: All specifications include baseline covariates from preceding tables: farmer demographics (age, gender), agricultural practices (input use), and other preintervention characteristics. Baseline health controls comprise symptom duration (days symptoms lasted), work disruption (days of work prevented), healthcare utilization (medical treatment sought and associated costs), and specific symptoms experienced during the baseline cowpea season. State fixed effects control for regional heterogeneity. Standard errors (in parentheses) are clustered at the community level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3. Exploring treatment effect heterogeneity

6.3.1. ANCOVA heterogeneity analysis

We begin by investigating HTEs using an ANCOVA framework that interacts with the pooled treatment indicator (combining T1 and T2) with key baseline covariates. Guided by prior work on technology adoption and heterogeneous returns (Beaman et al., 2021; Suri, 2011; Jack, 2013; Feder et al., 1985), we focus on characteristics likely to influence the realization of benefits of planting PBR cowpea: cowpea plot size, asset holdings, baseline yields, and gender of the plot manager. All models control baseline household and farm characteristics and include state fixed effects, with standard errors clustered at the community level to account for intracluster correlation. Results across six outcome domains, four related to insecticide use and two to health, are presented in Table 7.

Panel A: Plot size. Results generally indicate that treatment effects are larger for farmers with smaller plots. The main treatment effect is negative and statistically significant for *Maruca*-specific sprays (−1.230; $p < 0.01$) and insecticide volume (−1.261 l/ha; $p < 0.01$), indicating a substantial reduction in insecticide use targeted at *Maruca*. The interaction between treatment and large plot size is positive but not significant for total sprays (+0.389; $p > 0.10$), indicating that farmers with larger plots experience a smaller reduction in overall spray frequency, although the interactions are not statistically significant for all outcomes and the overall quantity of insecticides remains lower.

Panel B: Asset holdings. Treatment effects are again significant for the *Maruca*-specific outcomes, but the interaction terms indicate no significant differences among asset-rich farmers. While the main treatment effect is strongly negative for *Maruca* sprays (−1.253; $p < 0.01$) and volume (−1.188; $p < 0.01$), the interaction terms for asset-rich households are not statistically significant, implying that the health and environmental benefits of receiving PBR cowpea accrue broadly, with relatively greater gains among resource-constrained households.

Panel C: Baseline yields. Treatment effects on insecticide outcomes remain statistically significant across the board for *Maruca*-specific measures. The interaction term between treatment and higher yield is negative and not statistically significant for *Maruca*-specific insecticide volume (−0.079; $p > 0.10$), while positive but not significant for days unable to work (+0.044).

Panel D: Gender of the plot manager. Treatment reduces insecticide use and health burdens in Women-managed plots, with significant effects on insecticide use/ha (−1.969; $p < 0.05$) and *Maruca*-specific outcomes (for example, −1.398 for sprays, $p < 0.01$; and -1.647 for volume of insecticides, $p < 0.01$). The interaction term was significant for Maruca-specific insecticide volume (+0.768; $p < 0.10$). Taken together, these findings underscore that the benefits of receiving PBR cowpea are not evenly distributed: smaller, asset-poor, and Women-managed farms experience greater environmental and health gains, highlighting the importance of baseline constraints in shaping the returns to new agricultural technologies.

Table 7: ANCOVA heterogeneous treatment effects

	(1) Sprays (all pests)	(2) Insecticide use (l/ha)	(3) Sprays of *Maruca*	(4) Insecticide use of *Maruca*	(5) Days of symptoms	(6) Days prevented from working
Panel A: by level of plot size at baseline						
Any treatment (T1+T2)	-0.282	-1.085	-1.230***	-1.261***	-0.035	-0.026
	(0.177)	(0.864)	(0.234)	(0.270)	(0.123)	(0.077)
Large plot size	-0.080	-0.429	-0.235	-0.291	-0.039	-0.015
	(0.205)	(0.784)	(0.230)	(0.254)	(0.134)	(0.084)
Any treatment*Large plot size	0.389	-0.153	0.122	0.121	-0.065	-0.094
	(0.235)	(0.952)	(0.240)	(0.272)	(0.146)	(0.096)
Panel B: by level of asset holding at baseline						
Any treatment (T1+T2)	-0.058	-0.436	-1.253***	-1.188***	-0.058	-0.115
	(0.196)	(0.898)	(0.256)	(0.255)	(0.112)	(0.074)
Asset-rich	-0.105	0.710	-0.303	-0.148	-0.107	-0.110
	(0.204)	(0.953)	(0.269)	(0.274)	(0.121)	(0.067)
Any treatment*Asset-rich	-0.002	-1.446	0.233	0.035	-0.012	0.080
	(0.228)	(1.114)	(0.272)	(0.293)	(0.141)	(0.084)
Panel C: by level of yield at baseline						
Any treatment (T1+T2)	-0.055	-2.385	-1.131***	-1.117***	-0.050	-0.109
	(0.283)	(1.199)	(0.326)	(0.308)	(0.148)	(0.102)
Higher yield	-0.089	-1.554	0.012	0.074	0.023	-0.002
	(0.244)	(0.949)	(0.323)	(0.307)	(0.150)	(0.110)
Any treatment*Higher yield	0.019	1.731	-0.022	-0.079	-0.029	0.044
	(0.271)	(1.143)	(0.329)	(0.326)	(0.165)	(0.119)
Panel D: by level of baseline Women-managed plots						
Any treatment (T1+T2)	-0.141	-1.969**	-1.398***	-1.647***	-0.050	-0.022
	(0.221)	(0.932)	(0.262)	(0.277)	(0.110)	(0.043)
Women-managed plots	-0.055	-1.210	-0.306	-0.594**	0.009	0.105
	(0.202)	(0.780)	(0.269)	(0.271)	(0.128)	(0.073)
Any treatment*Women-managed plots	0.126 (0.230)	1.350 (0.926)	0.407 (0.268)	0.768* (0.289)	-0.033 (0.142)	-0.093 (0.079)

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 *** $p < 0.01$.

6.3.2. Identifying heterogeneous impacts with Causal Forests

While the ANCOVA interaction models reveal broad patterns of heterogeneity, they may overlook complex, nonlinear relationships among baseline characteristics. To formally test and quantify treatment effect heterogeneity, we next employ Causal Forest models to estimate CATEs at the individual level. Following Athey and Wager (2018), we summarize systematic variation in these CATEs using a BLP regression, which regresses predicted treatment effects on baseline covariates. The resulting R^2 and F-statistics provide omnibus tests of whether heterogeneity exists and whether observable characteristics explain it. The R^2 values range from 0.225 (health symptoms) to 0.622 (*Maruca*-specific sprays), with all F-statistics highly significant (p < 0.001) (Table 8). These results confirm that treatment effects of receiving PBR cowpea vary substantially across farmers, and that demographic, agronomic, and economic characteristics explain a meaningful share of this variation.

Table 8: Best Linear Predictor (BLP) test results for treatment effect heterogeneity

Outcome	BLP test R^2	F-statistic	*p*-value	Heterogeneity detected
Sprays (no.)	0.553	48.26	0.000	Yes
Insecticide (l/ha)	0.280	15.18	0.000	Yes
Sprays *Maruca* (no.)	0.622	64.21	0.000	Yes
Insecticide *Maruca* (l/ha)	0.578	53.31	0.000	Yes
Symptoms (no.)	0.225	11.34	0.000	Yes
Prevented from working (no.)	0.395	25.48	0.000	Yes

Notes: The BLP (Best Linear Predictor) 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. 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 $p < 0.001$.

6.3.3. CATE-stratified treatment effects

To further interpret this heterogeneity, we estimate GATEs across quintiles of predicted CATEs from a Causal Forest model. This approach allows us to assess whether the causal effects of receiving (rather than self-selecting into) PBR cowpea differ systematically across farmers with varying baseline characteristics. Figure 1 reports the estimated GATEs with 95 percent confidence intervals for pest management and health outcomes. Because treatment assignment in this experiment was randomized, and receipt of PBR cowpea was determined by the encouragement design, these results capture intention-to-treat (ITT) effects that are exogenous to unobserved preferences or risk attitudes. HTEs thus reflect differences in how distinct groups respond to receiving access to new technology, rather than selection bias in adoption decisions.

Insect pest management outcomes

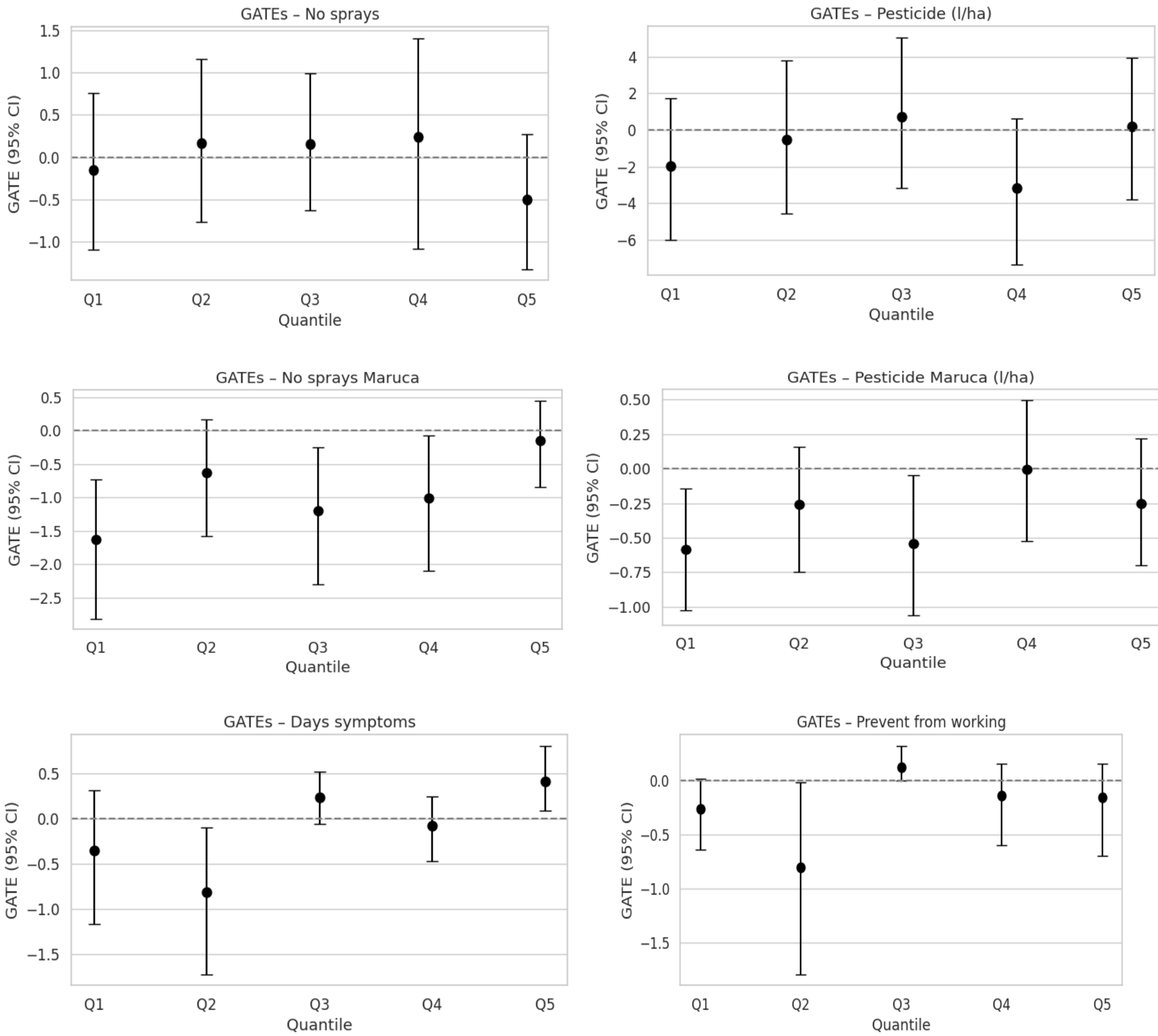
Across quintiles, total spray frequency shows no statistically significant effects, though point estimates are negative at the extremes (Q1 and Q5). Reductions in insecticide volume are largest in Q1 (−1.993 l/ha) and Q4 (−3.179 l/ha), though imprecisely estimated. In contrast, *Maruca*-specific outcomes show large and statistically significant declines in Q1, Q3, and Q4—consistent with selective behavioral substitution away from chemical sprays when a credible biological control option is received.

These results suggest that behavioral and resource constraints, rather than agronomic potential, drive responsiveness: farmers with tighter liquidity or labor constraints adjust their pest management practices most strongly when they receive PBR cowpea through intervention. From a theoretical standpoint, these results align with models of technology adoption under credit, information, and risk constraints (Feder et al., 1985; Suri, 2011; Jack, 2013). In such frameworks, treatment assignment (that is, receiving PBR cowpea seed) can be viewed as a shock to the cost or risk frontier that shapes optimal input use. Resource-constrained or risk-averse farmers, those with the steepest marginal costs of pesticide use, respond most strongly to receipt of the new technology. In the context of encouragement design, this corresponds to a heterogeneous ITT effect that is largest where constraints are tightest and potential input savings are greatest.

Farmers' health outcomes

The patterns in these results are consistent with theoretical models linking occupational exposure and productivity (Liu and Huang, 2013). In such settings, exogenous receipt of a low-chemical technology reduces health risks and labor disruptions, particularly for farmers who were initially most exposed to chemical use. The concentration of health benefits among the lower quintiles suggests that PBR cowpea functions as a quasi-public good, providing private welfare gains that are larger for vulnerable or high-risk households. Within an encouragement design, this implies that targeting strategies that prioritize constraint-bound or exposure-prone populations could amplify welfare and health gains.

Figure 1. GATES of PBR cowpea on insecticide use and farmers' health



Note: This figure displays Group Average Treatment Effects (GATEs) and 95 percent 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 a randomized controlled trial of PBR cowpea.

6.4. Explaining treatment effect heterogeneity

To understand the drivers of heterogeneous impacts from receipt of PBR cowpea, we estimate how individual-level responsiveness varies with baseline characteristics. Using a BLP regression, predicted CATEs from a Causal Forest model are regressed on preintervention covariates, identifying the demographic, agronomic, and economic factors most predictive of heterogeneity across seven outcomes: four related to insecticide use and three to health.

Heterogeneity in pest management outcomes is primarily associated with baseline spraying behavior, household resources, and age. Farmers who sprayed more at baseline were less responsive to the intervention ($p < 0.001$), reflecting entrenched pest control routines, whereas women-managed plots were more responsive ($p = 0.003$), and older household heads showed slightly lower responsiveness ($p = 0.032$). Higher baseline yields predicted smaller reductions in spraying, consistent with diminishing returns to improved technology among already productive farmers. Responsiveness in insecticide volume was concentrated among poorer, input-constrained households: smaller plots ($p = 0.013$) and lower baseline chemical use ($p < 0.001$) were associated with larger reductions, whereas wealthier households and older farmers maintained higher usage ($p < 0.001$; $p < 0.001$). *Maruca*-specific outcomes followed the same pattern, with reductions largest among farmers with lower baseline use and fewer assets, highlighting greater marginal responsiveness among resource-constrained households.

Heterogeneity in health outcomes mirrors these patterns. Reductions in days of symptoms were larger among younger household heads ($p < 0.001$) and women-managed plots ($p = 0.001$), while households with higher baseline insecticide use experienced smaller gains. Days prevented from working declined most among younger farmers and those with smaller plots (p = 0.001; $p = 0.004$), consistent with greater marginal benefits of exposure reduction for labor-constrained households. Across all health outcomes, lower baseline yields were associated with larger treatment effects, indicating that less-productive households captured the greatest non-yield benefits.

Taken together, these findings suggest that receipt of PBR cowpea generates heterogeneous impacts along dimensions of resource constraints, baseline productivity, and exposure risk, consistent with theoretical models of adoption under heterogeneous constraints (Suri, 2011; Feder et al., 1985). In a randomized encouragement design, these estimates reflect causal effects of receipt, revealing that health and environmental benefits are concentrated among more vulnerable farmers. Targeting interventions toward these populations could therefore enhance both the efficiency and equity of technology diffusion.

Table 9: Baseline covariates driving differences in treatment effects

Covariate mean	Coefficient	p-value
Panel A: Sprays all pests (no.)		
Age of household head	0.002	0.031
No. of sprays	0.065	0.000
Women-managed plot	0.078	0.003
Baseline yield	0.002	0.000
Panel B: Insecticide use (l/ha)		
Age of household head	0.017	0.000
Plot size	-0.040	0.013
No. of sprays	0.070	0.000
Pest (l/ha)	-0.032	0.000
Asset-rich	-0.653	0.000
Panel C: Sprays for *Maruca* (no.)		
Age of household head	0.004	0.001
No. of sprays	-0.081	0.000
Baseline yield	-0.001	0.000
Asset-rich	-0.099	0.002
Panel D: Insecticide use (l/ha) for *Maruca*		
No. of sprays	–0.036	0.000
Pest (l/ha)	0.004	0.000
Baseline yield	-0.000	0.000
Asset-rich	-0.042	0.003
Panel E: Days of symptoms		
Household size	-0.006	0.000
Age of household head	-0.002	0.000
Women-managed plot	0.034	0.001
Baseline yield	0.001	0.039
Asset-rich	0.021	0.042
Panel F: Days prevented from working		
Age of household head	-0.002	0.004
Plot size	-0.004	0.001
Pest (l/ha)	0.002	0.000
Baseline yield	0.001	0.001

Notes: Coefficients from a Best Linear Predictor (BLP) regression of individual-level Conditional Average Treatment Effects 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 preintervention in a randomized controlled trial.

7. Conclusions

This paper examines the impacts of receiving the PBR cowpea variety on insecticide use and health outcomes using data from a c-RCT with an encouragement design. On average, PBR cowpea receipt significantly reduces insecticide sprays and volumes, particularly targeting the *Maruca* pod borer, to which the variety confers resistance. These reductions lead to lower input expenditures and fewer self-reported health symptoms related to chemical exposure, consistent with prior evidence from *Bt* cotton and other GM crops in South Asia, which show welfare gains beyond yield and input cost savings (Ahmed et al., 2021; Kouser et al., 2019a).

To explore heterogeneity, we combine ANCOVA interaction models with machine learning–based Causal Forest estimates of Conditional Average Treatment Effects (CATEs). Results reveal substantial variation in both agronomic and welfare outcomes. Farmers who operate smaller plots, hold fewer assets, and face labor or liquidity constraints experience the largest reductions in *Maruca*-targeted spraying and insecticide volume, along with greater declines in pesticide-related illness and fewer days lost to sickness. In contrast, wealthier farmers or those with higher baseline spraying frequencies continue to use relatively high levels of insecticides but capture larger profitability gains, reflecting scale- and skill-biased responsiveness. Notably, total spray frequency does not uniformly decline following receipt of PBR cowpea, suggesting selective behavioral substitution: farmers with labor or liquidity constraints reduce chemical use when viable alternatives exist but may maintain spraying overall. This indicates that encouragement alone may be insufficient to fully shift entrenched pest management routines.

From a policy perspective, these results emphasize the importance of moving beyond average effects of receipt and simple seed distribution. Environmental gains may require targeting larger, wealthier farmers who apply insecticides at high rates, pairing PBR cowpea provision with information campaigns and regulatory incentives to discourage excessive use. In contrast, improving health outcomes is most relevant for smaller, less wealthy, and labor-constrained households. Supporting these groups through credit or savings programs, community seed schemes, and scale-appropriate mechanization (for example, Takeshima et al., 2025, 2020) may help to realize the full health and input-use benefits of receiving PBR cowpea.

Finally, integrating predictive analytics with field diagnostics allows interventions to account for labor availability, risk aversion, and liquidity constraints that influence how households respond to receiving PBR cowpea. Incorporating gender, plot size, and asset holdings into targeting strategies can improve both equity and efficiency. While women-managed plots and women-headed households were included in our study, impacts for these groups were only marginally significant, suggesting opportunities for gender-focused interventions (Galiè et al., 2025). In sum, receiving PBR cowpea in an encouragement design generates significant welfare gains, particularly for resource-constrained smallholders, but realizing the full potential of this technology requires nuanced, context-specific policies that extend beyond market-based interventions and address the diverse constraints facing smallholder farmers.

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