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Optimizing Public and Private Seed Systems: A Marginal Treatment Effect Analysis for Targeting Biofortified Bean Diffusion in Zimbabwe

Richard Alioma[1] | Gwaze Tinashe[2] | Halasi Gidongo Zech[3] | Bho Mudyahoto[4] | Mubiinzi Geofrey[5] | Kudita Sakile[2]

[1]HarvestPlus, Kampala, Uganda | [2]Alliance Bioversity-CIAT, Harare, Zimbabwe | [3]Muni University, Arua, Uganda | [4]Harvestplus IFPRI, Kampala, Uganda | [5]Uganda Martyrs University, Nkozi, Uganda

Correspondence: Richard Alioma (aliomarichards@yahoo.com)

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ABSTRACT

Understanding the full benefits of scaling the production and consumption of biofortified crops requires moving beyond estimates of average adoption to understand how returns vary across the heterogeneous population of growers of such varieties. We used a marginal treatment effect framework to optimize seed system targeting by analyzing the heterogeneous marginal benefits of adopting NUA45, biofortified beans in Zimbabwe. Using nationally representative data, we move beyond the population average to estimate the marginal returns for subgroups of farm households differentiated by their observed characteristics and latent resistance to adoption. Results indicate that scaling NUA45 generates positive returns for all marginal adopters, with benefits 1.3 percentage points higher among actual adopters than non-adopters. However, the analysis reveals that farm households with socioeconomic characteristics making them more likely to adopt, particularly those near the adoption threshold, gain disproportionately compared to those least likely to adopt. These findings provide an evidence-based strategy for optimizing public and private seed systems, where targeted diffusion strategies can maximize social returns by prioritizing farmers with a moderate-to-high propensity to adopt. Meanwhile, households least likely to adopt may require complementary support to achieve an equitable impact. This marginal treatment effect approach provides a novel blueprint for efficiently targeting the diffusion of biofortified seeds to maximize both scale and welfare.

摘要

要充分理解扩大生物强化作物生产与消费所带来的效益，不能仅停留在平均采纳率的估算上，而需深入探究种植此类品种的农户群体在收益上的异质性。本研究采用边际处理效应框架，通过分析津巴布韦农户采纳生物强化豆类品种NUA45时的边际收益异质性，旨在优化种子系统的推广目标定位。基于全国代表性数据，我们超越了总体平均水平，估算了根据可观测特征及潜在采纳意愿（或采纳阻力）划分的农户子群体的边际收益。结果显示，推广NUA45为所有处于边际采纳状态的农户均带来了正向收益，且实际采纳者的收益率比非采纳者高出1.3个百分点。然而，分析发现，那些因社会经济特征而更倾向于采纳（尤其是处于采纳临界点附近）的农户，其获益远超那些采纳意愿最低的农户。这些发现为优化公共与私营种子系统提供了基于证据的策略：通过针对采纳倾向中等至偏高的农户优先推广，可以最大化社会效益。与此同时，对于采纳意愿最低的农户，则可能需要配套支持措施，以确保产生公平的社会影响。这种边际处理效应方法为高效定位生物强化种子的推广提供了新思路，有助于在扩大推广规模与提升社会福利之间实现最大化平衡。

RESUMEN

Para comprender plenamente los beneficios de ampliar la producción y el consumo de cultivos biofortificados, es necesario ir más allá de las estimaciones de adopción promedio y analizar cómo varían los rendimientos entre la población heterogénea de agricultores que cultivan dichas variedades. En este estudio, utilizamos un marco de análisis de efectos marginales del tratamiento para

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optimizar la focalización de los sistemas de semillas, examinando los beneficios marginales heterogéneos derivados de la adopción de la variedad de frijol biofortificado NUA45 en Zimbabue. A partir de datos representativos a nivel nacional, superamos el promedio poblacional para estimar los rendimientos marginales en subgrupos de hogares agrícolas, diferenciados según sus características observables y su resistencia latente a la adopción. Los resultados indican que la expansión del cultivo de NUA45 genera rendimientos positivos para todos los adoptantes marginales; concretamente, los beneficios son 1,3 puntos porcentuales mayores entre quienes efectivamente adoptan la variedad frente a quienes no lo hacen. No obstante, el análisis revela que los hogares agrícolas con características socioeconómicas que favorecen la adopción, especialmente aquellos situados cerca del umbral de adopción, obtienen beneficios desproporcionadamente mayores en comparación con aquellos con menor probabilidad de adoptar. Estos hallazgos ofrecen una estrategia basada en evidencia para optimizar los sistemas de semillas públicos y privados, permitiendo que las estrategias de difusión focalizada maximicen el retorno social mediante la priorización de agricultores con una propensión moderada o alta a la adopción. Por otro lado, los hogares con menor probabilidad de adoptar podrían requerir apoyo complementario para lograr un impacto equitativo. Este enfoque de efectos marginales del tratamiento proporciona un modelo innovador para dirigir de manera eficiente la difusión de semillas biofortificadas, maximizando tanto la escala de adopción como el bienestar.

1 | Introduction

The potential of biofortified crops to reduce micronutrient deficiencies at the population level is contingent on their widespread adoption and production. Many countries have integrated biofortification into their policies, encompassing nutrition, breeding programs, and public procurement initiatives, such as school feeding. Finding the returns on these investments is critical for effective scaling. A growing body of literature reveals the existence and importance of heterogeneous treatment effects in farming populations, underscoring the need to understand these effects as biofortified iron beans are scaled up in Zimbabwe. For instance, Funes et al. (2019) found that adopting iron-biofortified beans increased yield and income by over 23%. In contrast, other reviews note a potential trade-off between micronutrient density and yield (van Ginkel and Cherfas 2023). Further complicating the picture, Michler et al. (2019) demonstrated that farmers could earn significantly higher profits from improved chickpeas without significant yield gains, highlighting that benefits extend beyond production. Therefore, analyzing the marginal returns to adoption of any new variety/technology, as shown by Mellon Bedi et al. (2022), is essential for informing policy choices on which varieties to scale.

Biofortification, the process of improving the nutritional content of staple crops through conventional breeding, is a strategic investment in public health. This is particularly important for rural populations who often have limited access to supplements, industrially fortified foods, and the dietary diversity found in urban areas (Bouis and Saltzman 2017). Its impact pathway is distinctly agricultural; by focusing on smallholder farmers who are both micronutrient-deficient and dependent on their own harvests for food, it directly incorporates nutrition into the food system (Petry et al. 2018). When farmers grow and eat biofortified crops, this results in improved nutritional and health outcomes over the medium to long term (Saltzman et al. 2017). However, for policymakers, understanding the short-term economic advantages is also essential, raising an important policy question: What are the immediate economic returns of adopting biofortified crops, and which populations should be prioritized to maximize this impact?

Whereas past research on iron bean varieties has demonstrated average benefits, including increased yields, incomes, and improved nutrition (Funes et al. 2019; Vaiknoras and Larochelle 2021), these studies primarily employ methods that estimate average treatment effects (ATE) across entire populations. This approach overlooks important variations in outcomes among different farmer subgroups. As a result, there is little empirical guidance on how to target diffusion strategies to maximize impact effectively. The literature has not identified which farmer categories based on observable traits and resistance to adoption should be prioritized by seed systems to optimize social and economic returns. This research addresses this gap by using a marginal treatment effect (MTE) framework to move beyond average estimates and develop an evidence-based strategy for targeting the diffusion of biofortified seed, ultimately guiding the allocation of limited resources to achieve greater reach and welfare.

Our research enhances the literature on biofortified crop adoption across three main areas. Firstly, empirically, we show that the adoption of NUA45 beans in Zimbabwe is motivated by a yield advantage that increases both consumption and income, building on findings from other regions (Vaiknoras and Larochelle 2021). Secondly, methodologically, we fill a gap by employing the MTE framework. Although studies using instrumental variables (IV) or endogenous switching regressions report positive average returns, they do not reveal how benefits vary among different target categories. The MTE approach (Heckman and Vytlacil 2005) uniquely identifies returns for farmers at the adoption margin, helping explain low overall adoption rates and guiding targeted policies (Sarr et al. 2021). Thirdly, we incorporate and measure the influence of perceptions of nutritional traits on adoption, extending Muthini (2018) and Asiedu–Darko (2014) to demonstrate that perceived nutritional benefits are a key behavioral factor that is often overlooked in studies focused solely on agronomic or economic responses.

This paper is structured as follows. Section 1 offers essential background on micronutrient deficiency in Zimbabwe and the adoption of NUA45 biofortified beans. Section 2 describes the

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survey approach, the data collected, and the main estimation method, including the MTE framework. Section 3 presents empirical results that identify the factors driving adoption, differences in returns, and policy finding. Finally, Section 4 discusses policy recommendations for dividing roles between public and private seed systems to enhance both the impact of scaling up biofortified crops in Zimbabwe.

2 | Methodology

2.1 | Data Sources

We used data from a national farmer survey conducted in Zimbabwe in 2022. The sample was drawn from a 2021 crop assessment frame provided by the Ministry of Agriculture. We selected all Wards with more than 45 ha of common bean area, which together cover 80% of Zimbabwe's total bean land area. From these, we randomly chose 85 wards and 126 villages. Data collection occurred in two phases from October to November 2022. First, we listed all households in the sampled villages to identify eligible respondents—bean farmers who had grown iron-biofortified beans at least once since 2015. In the second phase, a structured questionnaire was administered face-to-face using computer-assisted personal interviewing (CAPI).

2.2 | Theoretical and Empirical Framework

Our theoretical framework combines the Generalized Roy Model of self-selection (Heckman and Vytlacil 2007) with insights from behavioral economics on technology adoption (Kahneman and Tversky 1979) and diffusion theory (Rogers 1995; Feder et al. 1985). The Roy model forms the core economic basis, suggesting farmers adopt when their expected gains surpass their personal threshold, accounting for both observed and unobserved differences. Behavioral economics adds that perceptions, risk preferences, and social learning influence decisions, creating latent resistance even when economic returns are favorable. Diffusion theory clarifies why early adopters differ from laggards. Structural barriers, such as limited resources or market access, can create persistent adoption gaps despite benefits. This integrated approach predicts patterns of sorting based on gains, highlights perceptions' influence on adoption, and identifies "high-return, reluctant adopters" as key targets for policy.

Estimating the true returns to adopting NUA45 beans is challenging due to selection bias. Farmers who choose to adopt may differ systematically from non-adopters in both observable (farm size and education) and unobservable (skill and motivation) characteristics. Standard methods like IV address some of this bias. However, to fully account for selection on unobservable traits and estimate how returns vary across farmers, we use the MTE framework developed by Heckman and Vytlacil (2007). The MTE framework has three key advantages. First, it models selection using a latent index that incorporates both observed and unobserved factors. Second, it provides a unified model from which common parameters, like the ATE, can be derived. Third, it estimates treatment effects for farmers at the margin of adoption—those who are indifferent or hesitant. This is critical for designing policies that encourage new adopters.

2.2.1 | The Generalized Roy Model for Targeting

We implement the MTE framework using a generalized Roy model. This model separates the analysis into an adoption decision and the potential outcomes (yield and income) under adoption and non-adoption.

Let $D_i = 1$ if farmer i adopted NUA45 and $D_i = 0$ otherwise. The observed outcome Y_i (yield/income) is as follows:

$$Y_i = (1 - D_i)Y_{0i} + D_i Y_{1i} \tag{1}$$

where Y_{1i} is the potential outcome if they adopt and Y_{0i} is the potential outcome if they do not. These are modeled as follows:

$$\begin{aligned} Y_{0i} &= \mu_0(X_i) + \epsilon_i \\ Y_{1i} &= \mu_1(X_i) + \epsilon_i + \eta_i \end{aligned} \tag{2}$$

Here, μ_0 and μ_1 are functions of observed farmer characteristics X_i (land and education). The error term ϵ_i captures unobserved factors affecting the baseline outcome. The term η_i represents the idiosyncratic gain from adoption that varies by farmer.

A latent index models the decision to adopt

$$\begin{aligned} I_{D_i} &= \mu_D(Z_i) - V_i \\ D_i &= 1[I_{D_i} > 0] \end{aligned} \tag{3}$$

Here, $\mu_D(Z_i)$ is a function of observed variables Z_i, which includes X_i and at least one IV. The term V_i is a continuous latent variable representing a farmer's unobserved resistance to adoption (risk aversion, distrust of new seeds). The vector Z_i include valid instrumental variables that affect the adoption decision but do not directly influence the outcome Y, other than through adoption. We use two instruments: village-level adoption rate, which influences an individual's decision through social learning and seed access, and distance to the nearest agrodealer, which affects the cost and ease of obtaining seeds but should not directly determine agricultural output for non-adopters.

A key feature of this model is that it allows for selection on unobserved gains. Farmers who expect higher benefits (η_i)—perhaps due to unobserved soil quality or entrepreneurial skill—are likely to have lower unobserved resistance (V_i). By estimating treatment effects across the distribution of V_i, we can estimate how returns differ for farmers with varying latent propensity to adopt.

2.2.2 | Defining the MTE for Policy

The core parameter of interest is the MTE. It is defined as the ATE for farmers with specific observed characteristics $X = x$ and a specific level of normalized unobserved resistance $U = u$, where U is the quantile of V.

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$$\mathrm{MTE}(x,u) = E\left[Y_1 - Y_0 \mid X = x, U = u\right] \quad (4)$$

The variable U ranges from 0 to 1. A farmer with $U = 0.1$ has very low unobserved resistance (high latent willingness to adopt), whereas a farmer with $U = 0.9$ has high resistance.

This framework is powerful because all common policy-relevant parameters—like the ATE or the effect on current adopters (TT)—can be calculated as weighted averages of the $\mathrm{MTE}(x,u)$ across different values of U.

For practical policy targeting, we simplify by conditioning on the propensity score $p = P(Z) = \Pr(D = 1 \mid Z)$, which summarizes observed drivers of adoption. We redefine a policy-centric MTE:

$$\widetilde{\mathrm{MTE}}(p,u) = E\left[Y_1 - Y_0 \mid P(Z) = p, U = u\right] \quad (5)$$

This tells us about the expected return for a farmer with a given observed adoption likelihood (p) and a given level of unobserved resistance (u). Plotting this function reveals which combinations of p and u yield the highest returns, providing a direct map for targeting.

2.2.3 | MTE to Policy-Relevant Effects

This framework allows us to calculate effects for specific policy changes. A key parameter is the marginal policy-relevant treatment effect (MPRTE). It answers the question: What is the average return for farmers who would be induced to adopt by a marginal change in policy (a small subsidy or information campaign)?

Under our model, the MPRTE for farmers with propensity score p is as follows:

$$\mathrm{MPRTE}(p) = \widetilde{\mathrm{MTE}}(p,p) \quad (6)$$

It equals the MTE precisely at the margin where a farmer's unobserved resistance u equals their observed propensity score p—the point of indifference. By examining how $\mathrm{MPRTE}(p)$ changes with p, we learn whether scaling efforts should target farmers with high or low observed likelihood of adoption to maximize impact.

2.3 | Empirical Estimation Strategy

We estimate the model in two steps. First, the selection/adoption equation estimates a logit model to derive the propensity score, leveraging our instruments (village adoption rate and distance to an agrodealer) and control variables (such as farm size, irrigation access, and gender). Second, the outcome equation employs semiparametric local polynomial regression to estimate the surface without restrictive functional form assumptions. This approach provides flexibility in understanding how returns change with respect to certain variables. Control variables included in the outcome equation encompass production factors (land and labor) and demographic attributes (age and household size), which influence yield or consumption or income but are unaffected by the instruments. Such a method helps us map the varied returns to NUA45 adoption, offering a data-driven blueprint for optimizing seed system targeting in Zimbabwe.

3 | Results

3.1 | Descriptive Statistics

The descriptive statistics indicate that adopting the NUA45 bean variety is associated with higher yields but lower average monthly agricultural revenue than non-adopters (Table 1). This difference in yield could partly result from systematic disparities in farm inputs and socioeconomic factors, which may cause selection bias. Specifically, NUA45 adopters tend to participate more in agricultural programs, have higher rates of plot irrigation, and be older. Conversely, non-adopters were characterized by larger farm sizes, greater livestock ownership, a higher productive asset index, and more frequent participation in community groups. This profile aligns with the finding that most non-adopters belonged to the A2 land category, where farm sizes range from 20 to 1500 ha, and the LFSP project was not systematically implemented. In contrast, many adopters were from female-headed households, a group that typically operates smaller landholdings in the A1 category where farm sizes range from 5 to 20 ha. These important covariates suggest that the differences in yield and revenue are not solely due to the adoption of NUA45. To better understand the true effect of adoption, we use a logit regression model to control for these confounding factors.

3.2 | Determinants of NUA45 Adoption

The factors influencing NUA45 adoption were examined using a logit model, with Table 2 showing the average marginal effects. Access to irrigation emerged as the strongest predictor, increasing the likelihood of adoption by 23.3 percentage points and underscoring its vital role in mitigating production risks. Adoption rates are also notably higher among female-headed households, indicating gender-specific preferences for nutrition-sensitive crops. Additionally, both the education level and age of the household have positive yet modest effects, suggesting that greater knowledge and farming experience help lower adoption barriers.

Several unexpected patterns emerged from the adoption model. First, a greater distance to agrodealers was associated with a higher likelihood of adoption. Although this may reflect targeted outreach in remote areas, it is also plausible that it captures the effect of free seed distribution to poor, smallholder households—particularly female-headed ones—which were prioritized by such programs. Second, wealthier households and those with larger landholdings were less likely to adopt. This supports the interpretation that smallholders and less wealthy families may prioritize NUA45 for household nutrition. However, an alternative explanation is that wealthier, market-oriented farmers may be less reliant on informal seed sharing (farmer-to-farmer

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TABLE 1 | Differences in mean characteristics of adopters and non-adopters in NUA45 practices.

Variable	Pooled $N=1138$	Adopters $N=376$	Non-adopters $N=762$	Difference	p
Fertilizer (kg)	208.27	223.94	200.54	23.40	0.10
Land (ha)	2.49	2.03	2.71	−0.68	0.00
Use of irrigation (1 = yes)	0.11	0.20	0.06	0.15	0.00
Perception of reliability of rain (1 = reliable)	0.45	0.50	0.43	0.07	0.02
Training (1 = yes)	0.60	0.62	0.59	0.03	0.31
Group participation (1 = yes)	0.29	0.24	0.31	−0.07	0.02
Sex (1 = female)	0.48	0.58	0.43	0.15	0.00
TLU	5.15	4.52	5.45	−0.93	0.02
Education	9.35	9.41	9.33	0.08	0.66
Household size	5.10	5.10	5.10	0.00	1.00
Asset index	−0.01	−0.23	0.10	−0.33	0.00
Seed company (1 = yes)	0.47	0.42	0.50	−0.08	0.01
Age of HH head (years)	46.51	48.19	45.68	2.51	0.00
Instruments					
Distance to the agrodealer (km)	45.20	51.23	42.23	9.00	0.01
Participation intensity	56.26	61.20	53.82	7.38	0.00
Number of extension visits	3.96	3.84	4.01	−0.17	0.05
Outcomes					
Agricultural income per month	316.66	282.74	333.39	−50.66	0.02
Bean income (dollars)	122.06	128.25	119.01	−9.24	0.43
Yield (kg/ha)	993.49	1022.05	979.40	42.65	0.47
Consumption (kg/P/year)	17.14	14.14	18.62	4.48	0.07

Note: The Mann–Whitney test and the chi-square test were used for the continuous and binary variables, respectively.

[F2F]), which tends to be more prevalent in poorer communities, as observed in comparative studies between Rwanda and the Eastern Democratic Republic of Congo. In contrast, wealthier farmers may prefer cash crops. Factors such as fertilizer use, training, and extension services showed no significant impact, suggesting that standard agricultural support programs do not specifically influence the adoption of this biofortified variety. Overall, these findings indicate that adoption is driven by a complex interaction among gender, risk management, and asset structure, rather than by traditional agricultural extension efforts alone.

3.3 | Returns on NUA45 Adoption

The MTE framework relies on common support, meaning that individuals with the same observable traits must have a positive probability of being either adopters or non-adopters of NUA45 (Caliendo and Kopeinig 2008). Figure 1 displays the propensity score distributions for both groups, indicating significant overlap across most of the spectrum. This demonstrates a robust region of common support, which is essential for accurate MTE estimation.

Table 3 shows the effects of NUA45 adoption on bean yield, household income, and bean consumption. For yield, a clear pattern of positive sorting emerges where the average treatment effect on the treated (ATT = 776 kg) is higher than the average treatment effect (ATE = 480 kg), which in turn is higher than the average treatment effect on the untreated (ATU = 329 kg). This suggests that farmers who adopted NUA45 generally had higher potential returns than a typical farmer in the population, and even non-adopters would have experienced notable yield improvements. Although these differences are modest, they are statistically significant, indicating that varying return levels influenced adoption. The significant and positive ATU is particularly noteworthy, in contrast to the findings of Carneiro et al. (2011), who report an ATU near zero. For household income

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TABLE 2 | Determinants of NUA45 bean adoption: Average marginal effects from logit model.

Variables	Marginal effect
Production factors	
Fertilizer (kg)	0.000036
	(0.000062)
Land (ha)	−0.044
	(0.031)
Land^2	0.0017
	(0.0047)
Irrigation use (1 = yes)	0.233***
	(0.038)
Reliable rain perception (1 = yes)	0.059*
	(0.027)
Household characteristics	
Household head is female (1 = yes)	0.093***
	(0.027)
Household head age (years)	0.0026**
	(0.0010)
Household head education (years)	0.0098*
	(0.0048)
Household size	0.0089
	(0.0057)
Asset index	−0.036*
	(0.016)
Tropical livestock units (TLU)	0.00071
	(0.0027)
Institutional and access factors	
Received training (1 = yes)	0.018
	(0.028)
Group participation (1 = yes)	−0.026
	(0.030)
Linked to seed company (1 = yes)	−0.0090
	(0.027)
Number of extension visits	−0.013
	(0.010)
Participation intensity	0.00174***
	(0.00038)
Distance to agrodealer (km)	0.00099***
	(0.00026)
Observations	1138

Note: The dependent variable is a binary indicator for NUA45 adoption (1 = adopter, 0 = non-adopter). Estimates are average marginal effects derived from a probit model. Standard errors are reported in parentheses below each coefficient. Statistical significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

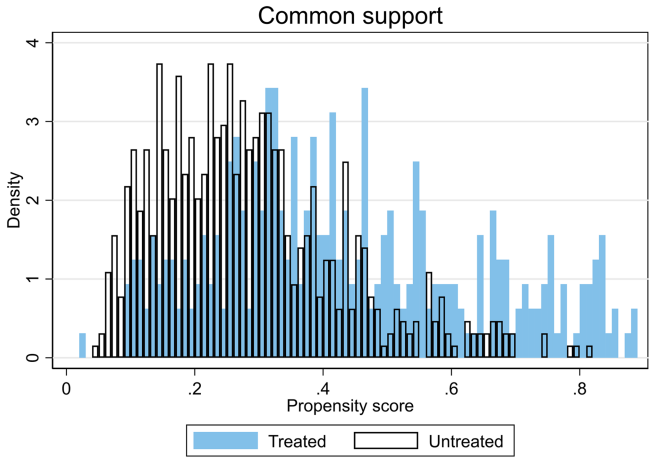


FIGURE 1 | Region of common support between adopters and non-adopters of NUA45.

and bean consumption, this pattern (ATT > ATE > ATU) was not observed.

3.4 | Scaling-Up Policy Effects of NUA45

To inform scalable interventions, we estimate MPRTEs, which measure the benefits of policies that selectively shift the adoption curve. We simulate four policy scenarios, namely, a uniform increase in adoption of NUA45 (A). This progressive policy boosts adoption mainly among households with a high baseline likelihood of adopting NUA45 (B), a targeted policy aimed at households with a low propensity to adopt NUA45 (C), and a focus on the "marginal" group (D) with a moderate (25%) likelihood of adopting NUA45. This approach extends beyond the ATE to address an urgent economic question: Should scaling efforts emphasize broad subsidies (such as seed vouchers), targeted support for early adopters, or specialized initiatives for disadvantaged households?

Table 4 presents the MPRTE estimates for promoting NUA45 adoption among farm households, demonstrating how policy design substantially influences agricultural productivity outcomes. The analysis reveals that uniform expansion strategies yield modest gains: a policy that proportionally increases adoption probabilities for all farmers (Policy A) generates an MPRTE of 264.44 kg/ha. In contrast, targeted approaches prove more effective. Specifically, a policy targeting farmers with adoption propensities below 25% (Policy C) yields a significantly higher increase of 291.75 kg/ha (significant at the 10% level). This productivity premium for targeted scaling suggests that farmers with initially lower likelihood of adoption exhibit greater marginal returns to the intervention. Figure 4 further elucidates this heterogeneity by illustrating how different policy rules alter the composition of marginal adopters. These findings, which account for essential heterogeneity through a semiparametric MTE framework, align with theoretical expectations from the selection model literature (Brand and Xie 2010), confirming that policies prioritizing "less-likely adopters" can enhance allocative efficiency in the diffusion of agricultural technology. Interestingly, whereas

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yield effects are consistently positive, income effects appear negative across specifications, indicating potential offsetting mechanisms that warrant further investigation.

3.5 | Targeting Policies for Maximum Impact

Based on the MTE framework of Zhou and Xie (2020), our analysis of the MPRTE reveals valuable insights into how different households benefit from scaling policies. It is fascinating to see significant variation—some households gain more than others—which aligns perfectly with the idea of essential heterogeneity discussed in the theoretical model. Specifically, our semiparametric estimates of MPRTE(p)—where p is the observed likelihood of adoption—show that households with the lowest propensity scores (p) see the largest improvements in both yield and consumption when adopting NUA45 biofortified beans (see Figure 2). This aligns well with the redefined MTE framework, which highlights that treatment effects tend to change along the propensity score, especially at the point of adoption where u = p. Figure 2 vividly illustrates that households with a low chance of adopting—often due to resource limitations like smaller land sizes or less access to markets—are the most responsive to small policy nudges.

TABLE 3 | Estimated mean impacts of adopting NUA 45.

Parameter	Yield (kg/ha)	Consumption (kg/capita/year)	Income (USD)
ATE	480.71**	7.31*	−78.96
	(290.23)	(6.39)	(74.57)
ATT	776.47*	3.95**	−132.81
	(465.21)	(1.76)	(125.29)
ATU	329.92*	8.99*	−51.33
	(292.59)	(7.55)	(90.56)

Note: Nonparametric bootstrap standard errors in parentheses (500 replications). ***, **, and * significance at 1%, 5%, and 10% levels, respectively. Estimates were based on MTE(p,u).

TABLE 4 | Estimated benefits of scaling up NUA45 adoption.

Variable name	Type	Yield (kg/ha)	Consumption (kg/capita/year)	Income (USD)
mprte: 1	A	264.44*	0.21	−75.15
		(233.24)	(6.38)	(60.40)
mprte: p	B	315.29**	0.35	−55.79
		(227.45)	(5.76)	(51.72)
mprte: (1—p)	D	238.51	0.14	−85.02
		(252.61)	(7.00)	(67.48)
mprte: I ($p < 0.3$)	C	291.75*	2.59	−106.50
		(276.76)	(10.24)	(97.43)

Note: Nonparametric bootstrapped standard errors in parentheses (500 replications). ***, **, and * significance at 1%, 5%, and 10% levels, respectively. The MPRTE(p) was estimated using the robust semiparametric approach.

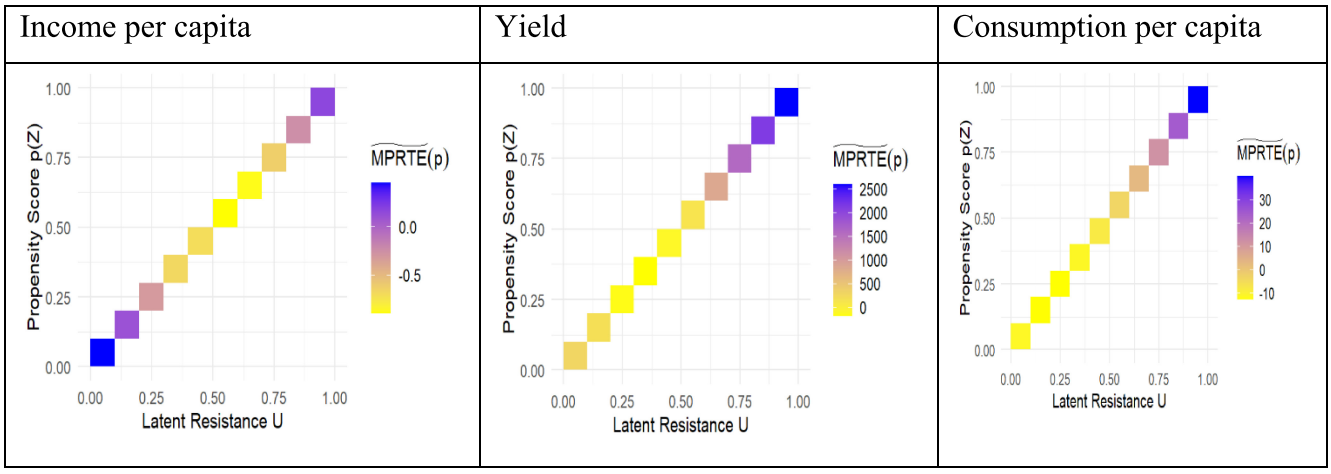


FIGURE 2 | Semiparametric estimates of MPRTE.

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This suggests that their unobserved resistance (U) is relatively low compared to the potential gains, leading to high returns from targeted interventions. So, policies that reduce barriers to adoption—such as seed subsidies, information campaigns, or improved access to agrodealers—are likely to provide the large effects for the intervension.

This heterogeneity underscores a critical policy insight: A uniform, untargeted scaling strategy would be inefficient. Instead, the success of scaling biofortified beans depends on a differentiated targeting approach that prioritizes households with low-to-moderate propensity scores, where latent returns are high but observable constraints inhibit adoption. Such an approach not only maximizes productivity and nutritional impacts but also enhances the equity and cost-effectiveness of public and private seed systems.

3.6 | Heterogeneity in Treatment Effects

Our analysis of the MTE reveals significant heterogeneity in the returns to NUA45 adoption, driven by both observed and unobserved factors. Figure 3 shows a downward-sloping MTE curve with respect to latent resistance (*u*), indicating positive selection on unobserved gains farmers with lower unobserved resistance achieve higher yields and incomes. This pattern reflects self-selection based on unobserved ability. Furthermore, at any given propensity score (*p*), farmers with lower *u* realize greater gains, confirming "sorting on gains," though this relationship reverses for household consumption. Notably, higher observed propensity to adopt (*p*) is also associated with greater benefits, underscoring the joint role of observable and unobservable factors in adoption efficiency. Together, these results demonstrate that returns to NUA45 are unevenly distributed, concentrating among farmers with favorable traits and low latent resistance. At the same time, Figure 2 illustrates how marginal returns vary across the propensity score spectrum, informing targeted policy design.

The analysis reveals a counterintuitive yet policy-relevant pattern: the MPRTE decreases as the observed propensity to adopt (p) increases (Figure 4), indicating that farmers are less likely to adopt based on observable traits but may derive greater benefits from adopting NUA45 beans. This inverse relationship is driven by strong negative selection on unobserved gains—farmers with high latent returns often exhibit lower observed adoption scores due to constraints such as limited assets or market access. As illustrated in Figure 2, the highest marginal returns in yield and consumption are concentrated among households with the lowest propensity scores. Therefore, directing interventions toward these "high-return, reluctant" farmers—rather than those already inclined to adopt—can optimize the impact of scaling efforts. This strategy is visually supported by the superior outcomes of targeted diffusion policies, as shown in Figure 4.

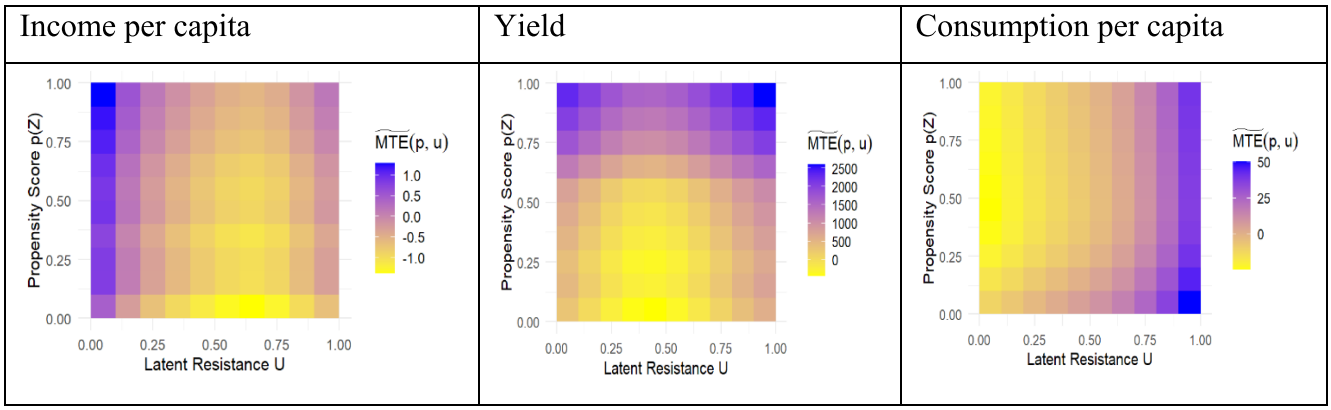


FIGURE 3 | Treatment effect heterogeneity based on semiparametric estimates of MTE(p,u).

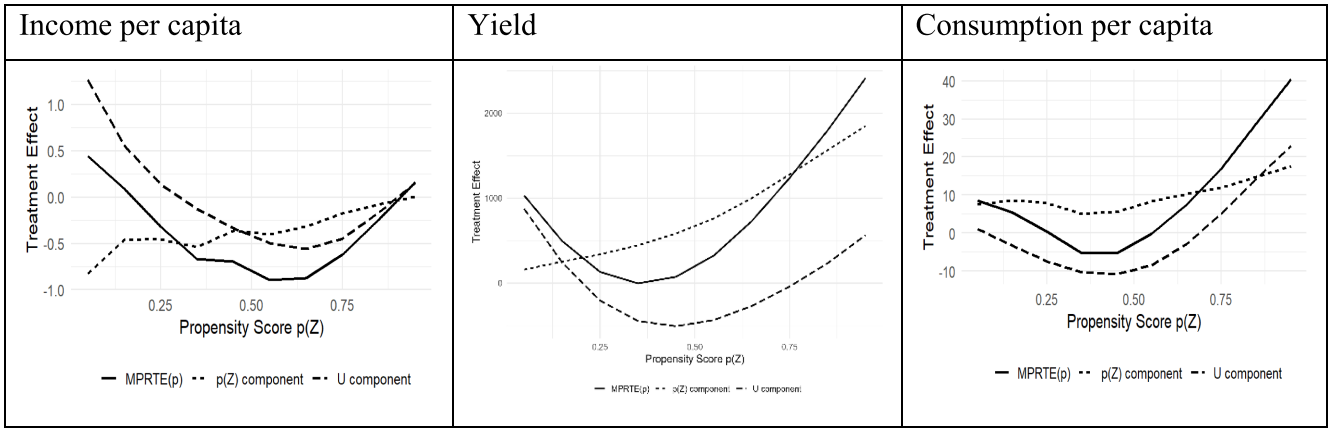


FIGURE 4 | Decomposition of MPRTE(p) based on semiparametric estimates of MTE(p,u).

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3.7 | Discussion

Our analysis clearly demonstrates positive selection on unobserved gains. The declining MTE curve and the pattern where the ATT is higher than the ATU suggest that farmers with greater unobserved returns—possibly due to unmeasured entrepreneurial skills, better micro-climates, or complementary management practices—were more likely to adopt NUA45. This "sorting on gains" pattern is typical of technology adoption amid significant heterogeneity (Heckman and Vytlacil 2001; Carneiro et al. 2011), indicating that early adopters self-selected based on their comparative advantage. This supports the rational actor model in the generalized Roy framework and confirms that adoption was driven by strategic decision-making rather than randomness.

The most policy-relevant insight comes from analyzing marginal entrants. Surprisingly, despite the positive selection pattern, the MPRTE decreases as the propensity score (p) rises. This presents a paradox: Farmers at the margin of indifference, who seem less likely to adopt due to observable traits such as smaller land sizes and fewer assets, stand to gain more from adoption. This counterintuitive result, also seen in other sectors (Brand and Xie 2010), occurs because the negative link between unobserved resistance (U) and potential gains outweighs the positive association between observed traits and baseline outcomes. Essentially, the smallholders who seem hesitant have high unobserved returns that are currently hidden by their apparent constraints.

This finding directly challenges a simple scaling approach that targets only farmers with a high willingness to adopt. Instead, it supports a two-pronged targeting method. Development work on promotion of iron beans gives higher priority to farmers with low-to-moderate observed willingness but low underlying resistance. These "high-return, reluctant adopters" face constraints that can be addressed through targeted support, such as seed subsidies, vouchers, or credit. Investing in this group provides the greatest marginal returns on public funds, boosting productivity and nutrition. Our MPRTE estimates show that policies targeting farmers with a propensity yield of less than 25% nearly double the returns of a uniform expansion (15.5% vs. 8.3%). Private seed companies can confidently target farmers with a high propensity to adopt, as these farmers are more likely to adopt and often better equipped with the necessary resources. Our findings suggest this group self-selects, reducing the need for public subsidies and enabling private firms to focus on market-driven distribution.

Our findings on the factors influencing adoption help clarify this strategy further. The significant positive impact of female-headed households on adoption highlights the need for gender-sensitive approaches, consistent with research indicating women tend to prioritize nutrition-sensitive crops (Vaiknoras and Larochelle 2021; Muthini 2018). The positive link between distance to agrodealers and adoption likely results from targeted outreach programs in remote areas, a method worth studying and replicating.

Methodologically, this study demonstrates the greater policy relevance of the MTE framework compared with traditional methods that estimate only ATE. Although researchers such as Funes et al. (2019) and Vaiknoras and Larochelle (2021) have confirmed that biofortified beans are effective on average, our approach reveals who benefits most at the margin, providing a blueprint for targeting, as suggested by Mellon Bedi et al. (2022). By explicitly considering unobserved selection, we prevent the common mistake of misallocating resources based on confounded average effects, a risk in analyses that overlook this heterogeneity (Sarr et al. 2021).

The positive and significant ATU for yield is an important finding. It shows that even those who do not adopt NUA45 can see considerable yield improvements, which differs from some earlier studies (Carneiro et al. 2011). This implies that the main obstacles for this group are not primarily related to whether the technology is agronomically suitable, but rather due to other constraints, such as limited information, financial liquidity, or risk aversion. This underscores the need for targeted policies to address these specific barriers among non-adopters, who could benefit greatly.

4 | Conclusions and Policy Implications

This study demonstrates that the scaling of biofortified crops depends not only on confirming their average benefits but also on understanding for whom these benefits are most significant. By applying a MTE framework to the adoption of NUA45 biofortified beans in Zimbabwe, we go beyond conventional analyses to estimate heterogeneous returns. Our main finding indicates that, although there is clear evidence of positive selection on unobserved gains, where early adopters possess the highest inherent returns, the most effective approach for scaling involves targeting a different group of farmers at the margin with a low-to-moderate observed propensity to adopt. These "high-return, reluctant adopters" constitute the most productive focus for public investment, as they provide the highest marginal returns when supported.

The analysis results in three core conclusions with direct policy relevance. First, a uniform, untargeted scaling policy is inefficient. Our MPRTE estimates reveal that a policy focused on farmers with a low propensity to adopt (below 25%) generates a yield return (15.5%) nearly double that of a uniform expansion policy (8.3%). This demonstrates that resource allocation based on heterogeneous returns can dramatically increase the impact of public and donor investments. Second, the findings provide a clear, evidence-based rationale for segmenting roles within the seed system. Public agencies and NGOs should prioritize farmers with low-to-moderate propensity scores, who face observable constraints (e.g., limited assets and market access) but have high latent returns. Interventions should include targeted seed subsidies, vouchers, and credit programs designed to overcome these specific barriers. Concurrently, private seed companies can efficiently serve the high-propensity segment, who are already inclined and able to adopt through market channels, thus ensuring commercial sustainability. Third, the determinants of adoption show that success requires more than just demonstrating agronomic superiority. The significant influence of gender and the counterintuitive role of distance to agrodealers highlight the need

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for gender-sensitive strategies that leverage local networks. Furthermore, the positive and significant ATU confirms that non-adopters are not non-adopters due to a lack of potential benefit. Their barriers are likely informational, financial, or related to risk perception, necessitating complementary support services.

Our analysis shows that farmers mainly see NUA45 biofortified beans as important for household food security and child nutrition, rather than as a way to generate income. This view is supported by higher adoption rates among female-headed households and lower adoption among wealthier, market-focused farmers. Therefore, policy and outreach should focus on highlighting the nutritional benefits—especially for women and children—rather than pitching the crop as a cash crop. Wealthier farmers might need specific messages about market premiums or family health benefits. Although farmers often believe there is a trade-off between yield and nutrition, our data indicates that NUA45 provides a notable yield advantage (ATE = 480 kg/ha). Demonstrating this through plot trials and peer learning can help correct this misconception. Social factors also influence adoption; the bean is sometimes seen as a "poor person's crop," which could discourage status-conscious farmers but encourage poorer households when distributed through welfare programs. Its low-risk, simple cultivation also makes it accessible to smallholders, though this simplicity might cause farmers to overlook its nutritional value. Extension services should therefore emphasize the health benefits alongside their ease of cultivation.

The propensity score targeting uses indicators such as the asset index, land size, and gender to identify and support households with a 10%–40% likelihood of adopting. This group, the "high-return, reluctant" segment, is where public investments will be most effective. Create smart subsidies by replacing universal seed subsidies with targeted vouchers or matching grants for low- to moderate-income adoption groups. Second, take advantage of higher adoption among female-headed households by designing diffusion campaigns that are inclusive and emphasize nutritional benefits that women value highly. Third, focus last-mile distribution and marketing efforts on areas and farmer groups showing high propensity scores, indicating a strong market potential. Four, collaborate with public programs on initiatives such as "demonstration plots" in regions with low propensity scores to raise awareness and expand markets. Fifth, bridge the gap for non-adopters by providing extension services that address knowledge gaps and offering financial products to reduce perceived risks.

Although targeted subsidies and vouchers are crucial for initiating adoption among "high-return, reluctant" households, maintaining this progress requires a phased transition from direct public transfers to more sustainable channels, such as commercial, community, and institutional support. This involves a decreasing subsidy plan—full support in Year 1, 50% in Year 2, 25% in Year 3, and full cost coverage by Year 4—allowing farmers to see benefits and develop budgeting skills. Alongside this, a division of roles emerges, with private seed companies increasingly serving higher-propensity adopters. Public extension services focus on reaching low-resource households at the "last mile" and are complemented by farmer-to-farmer seed multiplier networks that leverage social ties, especially in poorer, female-headed communities, to facilitate low-cost diffusion. Embedding distribution within ongoing programs and health initiatives ensures continuity while fostering local seed value chains and agrodealer networks reduces transaction costs associated with distance and secures commercial seed availability after projects end. An essential element is an evidence-based monitoring system that tracks household "graduation" from subsidized to unsubsidized access, guided by our MTE framework. This enables policymakers to adapt support levels and duration, maximizing the impact of scarce public funds and ensuring that the entire process—from initial public support to private-sector engagement and community diffusion—is efficient and sustainable.

Author Contributions

Richard Alioma: investigation, conceptualization, methodology, investigation, formal analysis, visualization, writing – original draft preparation, writing – review and editing. **Gwaze Tinashe:** data curation, project administration, writing - review and editing. **Halasi Gidongo Zech:** writing – review and editing. **Bho Mudyahoto:** funding acquisition, resources, supervision, writing – review and editing. **Mubiinzi Geofrey:** methodology, validation, writing – review and editing. **Kudita Sakile:** conceptualization, funding acquisition, project administration, supervision, writing – review and editing.

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The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure S1:** Region of common support between adopters and non-adopters of NUA45. **Figure S2:** Decomposition of MPRTE(p) based on semiparametric estimates of MTE(p, u). **Table S1:** Differences in mean characteristics of adopters and non-adopters of NUA45 practices. **Table S2:** Determinants of NUA45 bean adoption: Average marginal effects from probit model. **Table S3:** OLS and IV estimates of NUA45 adoption on bean yield (kg/ha).

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