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Impact of Improved Maize Seed Adoption on Farm Yield in Benue State, Nigeria

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Abstract

This study examines the impact of improved maize seed varieties (IMVs) on farm yield among smallholder Benue state, Nigeria and identifies key determinants of adoption. Benue State is often referred to as "Food Basket", but has an average yield of less than 2 tons per hectare, compared to 8-10 tons per hectare that can be achieved under improved technologies. While previous nationally representative studies disguise local heterogeneity, this study focuses specifically on Benue State using primary cross-sectional data from 205 maize farmers. However, minimizing selection bias was carried out by matching adopters and non-adopters with similar observable characteristics and this method was introduced by using Propensity Score Matching (PSM) to estimate the causal impact of improved maize seed varieties (IMVs) adoption on maize yield. Nearest Neighbour Matching is used to compute the Average Treatment Effect on the Treated (ATET), with robustness checks using Radius and Kernel Matching. The results indicated that IMV adoption is significantly determined by gender (heads of male household), formal education, use of fertilizer, irrigation access, members of cooperative, and extension contact, emphasizing the significant roles of human capital, complementary inputs, as well as institutional support. Afterwards, the control of observable differences through matching led adopters to achieving a yield gain of 0.399 log-units which is relative to non-adopters that were not matched, and this is equivalent to 49% increase in output per hectare. The robustness across alternative matching algorithms is effective, compared with national-level evidence reporting a 38.7% yield increase [11]. Our finding suggests that the productivity of premium for IMVs may be greater in regions like Benue. The reliability of this treatment effect is confirmed using alternative matching algorithms in Robustness checks. Conclusively, the study of IMVs full potential is limited by inadequate access to quality seeds, complimentary inputs, funds, and gender-specific interventions.

Keywords: improved maize seed varieties (IMVs); farm yield; smallholder farmers; Benue state; propensity score matching (PSM); technology; Nigeria

1. Introduction

Benue state in Nigeria is widely recognized as one of the major regions for producing of maize (Zea mays L.), it is the most strategic staple crops that serves as food, feedstock and raw materials for millions of people in the country [1]. In Africa, Nigeria is ranked among the top producers of maize, yet the demand domestically exceed supply. Notwithstanding the general favorable agroclimatic conditions, the average yield nationally is stagnated to approximately 2.0 tonnes per hectare (t/ha), which is far below the usual agronomic potential of 7-10 t/ha achieved under optimized management [1]. This enduring gaps in yield reflects systemic failures in technology adoption in agriculture and a strong dependence on traditional, low input farming systems.

The central position of maize production landscape in Nigeria is attributed to Benue state which is often known as the "Food Basket of the Nation," exceeding 70% of producers being smallholder farmers that practice rainfed agriculture with limited input use. The topical climate of the state,

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annual rainfall of 1200-1800mm, and soils with sandy-loam creates suitable conditions for maize cultivation. Productivity in maize is constrained by many factors which leads to poor mechanization, limited access to improved seeds as well as insufficient institutional support that is far below potential.

Under optimal conditions, the National Variety Release Committee (NVRC) of Nigeria approved a collection of improved maize varieties that are stress-resilient, which includes, the SAMMAZ 51T-75T series with yields potential that approaches 10 tons per hectare. In spite of this, the empirical estimates shows that less than 40% of Nigerian smallholder farmers often utilize certified improved seed varieties, whereas majority rely continuously on local or recycled seeds [2]. This detaches on-form adoption that creates a key barrier to agricultural transformation between technological availability. The interaction of socioeconomic, institutional and financial factors is designed to influence adoption of improved agricultural technologies. However, the educational attainment improves a farmer's capacity to evaluate and adopt new technologies [3].

In addition, institutional factors like Information dissemination and social learning are facilitated by access to extension services and cooperative membership [2]. Also, many smallholder farmers are constrained from investing in improved inputs due to lack of credit [4]. The disparities among gender also added complex adoption barriers, having lower access to land, credit and information which is common with females [5,6].

Benue state despite being strategically important, lacks comprehensive micro econometric studies on the region based on the causal effects of IMV adoption. Previous research regularly depends on aggregated national data that doesn't realistically recognize the causal treatment effects. This study examines the gap by using Propensity Score Matching (PSM), a quasi-experimental design that controls for observable selection bias to evaluate the Average Treatment Effect on the Treated (ATET) of IMV adoption on maize yield in Benue State.

Particularly, this paper: (i) identifies the significant socioeconomic and institutional determinants of adoption in IMV. (ii) evaluates the causal yield impact of adoption using PSM together with Nearest Neighbor, Radius, and Kernel Matching algorithms, and (iii) it derives recommendation for policies in other to scale up adoption and therefore reduce yield gaps in Benue State and it is similar to smallholder farming system in Sub-Saharan Africa. This study contributes to the existing literature in three ways. First, it provides micro-level empirical evidence on the impact of improved maize seed adoption on farm yield among smallholder farmers in Benue State, Nigeria. Second, the study applies Propensity Score Matching (PSM), a quasi-experimental method that reduces selection bias and improves the reliability of causal inference compared to conventional regression approaches. Third, the study identifies key socioeconomic, farm-level, and institutional factors influencing adoption and provides policy-relevant recommendations for improving agricultural productivity and technology adoption in developing countries.

2. Literature Review

2.1. Importance of Maize and the Yield Gap in Nigeria

Maize (Zea mays L.) is a key player of agricultural economy in Nigeria. It functions as a crucial staple food, a core component of feeds in livestock, and a vital raw material for agro-based industries. Statistically, it predominates in the national cereal production and it is necessary to rural household livelihoods [7]. Regardless of the key importance, an absolute yield gap restrain productivity nationally. The national average yield of maize stagnates at approximately 2.0 ton/hectare which is far below the 7-10 ton/hectare, that is achievable under optimized research conditions when properly managed. These differences exhibit deficiencies in technology transfer, limited adoption of improved genetic materials, limited access to fertilizer and mechanization, as well as increasing climate vulnerability.

2.2. Technology Adoption Determinants

The decision-process calculus of smallholder regarding IMV adoption is influenced by a complex interaction of socioeconomic, institutional, and financial variables. Labour capital, measured by educational attainment, is experimentally established to improve a farmer's capacity to process information technically and assess the risk-return characteristics of novel technologies [3]. Institutional linkages, specifically access to agricultural extension services and membership in producer cooperatives, serving as key channels for information and social leaning, thus applying a decisive influence on adoption [2]. Prevalent credit and liquidity limitations often eliminate farmers from inputs market, notwithstanding the likelihood of large economic returns [4]. Intensifying these barriers are deeply rooted in disparities of gender, female farmers, who substantially contribute to production of maize, methodically face declined access to productive resources, extension contact and credit [5,6].

2.3. Productivity Impacts of Improved Varieties

Past studies have reviewed agricultural technology adoption farm in developing countries and they focused mainly on adoption determinant such as education, farm size, credit access, and extension services [8,9]. For example, empirical evidence indicates that improved maize seed variety adoption increases the productivity of farm, yielding gains of about 40-50 % as reported in African contexts [10] and a yield increase of 38.7% was found in Nigeria using data from national representative [11]. Even so, the effect of productivity depends on complimentary inputs like fertilizer and labour [12,13]. By methodology, selection bias is still a concern to estimate impacts of adoption, and Propensity Score Matching (PSM) has been used to address this issue and to obtain estimates that are more reliable [14]. Following this approach, this study employs Propensity Score Matching (PSM), while using farm-data from Benue State, Nigeria.

2.4. Conceptual Framework and Research Gap

This paper is theoretically is grounded in the Agricultural Household Model [15] and it offers a comprehensible framework for examining farm households that at the same time serves as units of production and entities of consumption which functions under market imperfections and liquidity constraints. The key theoretical relationship is that IMV adoption is likely to increase farm yield as well as providing seeds with developed genetic potential, better stress immunity, and efficiently resistance to pests and diseases, which is consistent with current meta-analytic findings [16].

In spite of productive work on adoption in agricultural technology and in Sub-Saharan Africa, the literature shows three leading research gaps: (i) scarcity of empirical evidence to Benue State, Nigeria's outstanding maize producing entity; (ii) insufficient studies using robust quasi-experimental designs that is capable to establish causal estimates; and (iii) scarcity of study on gender-differentiated patterns in adoption and productivity outcomes within the area. This paper directly addresses these gaps.

3. Materials and Methods

3.1. Study Area and Data Collection

This study was carried in Benue State, a north-central region in Nigeria and it is accounted for the highest production of maize. It lies between latitude 6025′-808′ N; Longitudes 7047′-10000′ E. The have a total land area of 30,800 km2, and it's organized into 23 Local Government Areas, with a probable population of approximately 6.14 million. Benue is bounded by the Republic of Cameroon, as well as other states like Nasarawa, Taraba, Cross River, Enugu and Kogi State. The area's tropical climate has 1200-1800mm annual rainfall with favorable sandy-loam soils.

In the study, primary data were collected by means of structured questionnaires through face-to-face interviews from a total of 205 respondents, including both adopters and non-adopters of

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improved maize varieties. The procedure introduced was multi-stage random sampling, for stage 1, local government areas producing maize were selected based on their intensity of production. In stage 2, communities in each Local Government Area were randomly selected, whereas, in stage 3, specific maize farmers were randomly selected from lists of extension service.

3.2. Variables and Measurement

Maize yield per hectare (t/ha) is the outcome variable and it is expressed in natural log form (ln_yield), in other to normalize the distribution. Also, the binary indicator of IMV adoption (1 = adopter, 0 = non-adopter) is the treatment variable.

The covariates include gender, education, age, age-squared (to capture non-linear effects), household size, land tenure, natural log of non-farm income (lnNFI), fertilizer use, access to irrigation, access to credit, membership of cooperative, and extension contact.

The table 1 below summarizes variable definitions, as well as measurements.

Table 1. Variable definitions and measurements.

Category	Variable	Definition and Measurement
Outcome	ln_yield	Natural log of maize yield per hectare (kg/ha)
Treatment	IMV adoption	1 = adopter of improved maize seed variety; 0 = non-adopter
Covariate	Gender	1 = male household head; 0 = female
	Education	1 = formal education attained; 0 = otherwise
	Age	Age of household head in years
	Age_sq	Age squared (non-linear effect)
	HH size	Number of household members
	Land tenure	1 = owner-operated land; 0 = otherwise
	lnNFI	Natural log of non-farm income (Naira)
	Fertilizer use	1 = uses fertilizer; 0 = does not
	Irrigation	1 = has access to irrigation; 0 = otherwise
	Credit	1 = has access to credit; 0 = otherwise
	Cooperative	1 = member of farmer cooperative; 0 = otherwise
	Extension	1 = received extension contact; 0 = otherwise

3.3. Empirical Method: Propensity Score Matching

In other to address potential bias that arises from non-random adoption of IMVs, the study applies Propensity Score Matching (PSM) [17,18]. The methodology generates statistical comparison of groups by matching treated (adopters) with controls (non-adopters), therefore, the counterfactual outcome can be approximated and supporting - causal inference.

Step 1: Propensity Score Estimation: Improved Maize Variety (IMV) adoption probability is estimated using a logistic regression model.

$$P(T_i = 1|X_i) = \frac{e\hat{}(\beta_0 + \beta_1 X_{1i} + \cdots + \beta_n X_{ni})}{(1+e)\hat{}(\beta_0 + \beta_1 X_{1i} + \ldots + \beta_n X_{ni})}$$

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where $T_i = 1$ is an indicator if farmer I adopts improved maize seeds and 0 otherwise; X_i is a vector of variable that influences adoption decision.

Step 2: Matching Procedure: Each of the adopter is matched with one or more non-adopters that have similar propensity scores using Nearest Neighbour Matching. Also, common support and covariate balance diagnostics are checked to ensure comparability between groups

Step 3: Treatment Effect Estimation: The Average Treatment Effect on the Treated (ATET) assess the causal yield difference between adopters and their matched non-adopters:

$$ATET = E[Y_1 - Y_0 | T = 1]$$

where Y_1 represent the potential outcome under adoption and Y_0 represent the potential outcomes under non-adoption.

Step 4 - Robustness Checks: Alternative matching methods which includes; radius matching with calipers of 0.01, 0.05, and 0.1 and Kernel Matching were employed to check the consistency and stability of the estimated treatment effects.

4. Results and Discussion

4.1. Descriptive Statistics

Table 2 shows a descriptive statistic for adopters and non-adopters of IMVs among socioeconomic, farm level, and institutional characteristics. The mean log-yield for adopters is 8.172 and it exceeds that of non-adopters, 7.7755, which provides preliminary evidence of a higher yield performance.

Adopters also tend to possess higher levels of formal education (51.4% compared to 25.9%) and are usually older on average, (44.71 vs. 38.75 years), indicating that both experience and human capital are significantly linked with adoption. Fertilizer use is positively higher among adopters (72.0%) than non-adopters (43.8%), which is consistent with the complementarity between improved seeds and adequate nutrient management [10]. A particularly striking difference is observed for irrigation access (67.3% of adopters vs. 25.9% of non-adopters), showing that water security is a pivotal enabling condition for IMV uptake. Cooperative membership (61.7% vs. 41.1%) and extension contact (67.2% vs 41.1%) are also significantly higher among adopters, showing the critical roles of institutional linkages and information access in driving technology adoption.

Table 2. Descriptive statistics of variables by adoption status (n = 205).

Variable	Unit	Non-Adopters Mean	SD	Adopters Mean	SD	Difference
ln_yield	kg/ha	7.755	0.699	8.172	0.537	0.417 ***
Gender	Male = 1	0.652	0.479	0.794	0.406	0.142 **
Education	Formal = 1	0.259	0.440	0.514	0.502	0.255 ***
Age	Years	38.75	11.745	44.71	11.325	5.96 ***
HH size	Members	5.759	1.988	5.822	1.647	0.063
Land tenure	Owner = 1	0.705	0.458	0.776	0.419	0.071
LnNFI	Naira	4.182	4.586	5.145	5.322	0.963
Fertilizer use	Yes = 1	0.438	0.498	0.720	0.451	0.282 ***

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Irrigation	Yes = 1	0.259	0.440	0.673	0.471	0.414 ***
Credit	Yes = 1	0.402	0.492	0.280	0.451	−0.122 *
Cooperative	Yes = 1	0.411	0.494	0.617	0.488	0.206 ***
Extension	Yes = 1	0.411	0.494	0.673	0.471	0.262 ***

Note: *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. SD = standard deviation.

4.2. Propensity Score Estimation (Logistic Regression)

Table 3 reveals the logistic regression results used in estimating the propensity scores. The model has a good moderate explanatory power (pseudo-R^2 = 0.293) and overall significance of $p < 0.001$, with crucial covariates exhibiting the expected directional effects.

Gender is positive and statistically significant at the 5% level (Coef. = 1.229), confirming that male farmers are more likely to adopt IMVs. This aligns with the broader literature on gendered resource access constraints in Sub-Saharan Africa [5,6,8].

Formal education demonstrably exerts a beneficial influence (Coef. = 1.420, $p < 0.01$), thereby underscoring the significance of human capital in promoting technology adoption; farmers with higher education levels are better prepared to understand extension communications and evaluate agronomic advancements. Age exhibits a positive, yet statistically non-significant, coefficient (0.203), accompanied by a negative age-squared term, which aligns with a concave relationship between adoption and age; however, neither term achieves significance, implying that institutional and resource considerations outweigh farmer life-cycle effects within this particular setting. Fertilizer application is positively and significantly correlated with adoption (Coef. = 0.799, $p < 0.10$), reflecting the complementarity between improved seeds and adequate nutrient management—IMVs typically achieve their yield potential only under sufficient fertilizer application. Irrigation access is the strongest predictor of adoption (Coef. = 1.593, $p < 0.01$), indicating that water security substantially increases a farmer's willingness to invest in higher-performing varieties. Cooperative membership (Coef. = 0.825, $p < 0.05$) and extension contact (Coef. = 0.955, $p < 0.05$) both significantly increase adoption probability, confirming the pivotal roles of collective action and information dissemination in technology diffusion. Credit access and household size are statistically insignificant, possibly reflecting small loan sizes, delays in disbursement, or the relatively modest labor demands of IMVs.

Table 3. Logistic regression results: Propensity score estimation.

Variable	Unit	Coefficient	Std. Error
Gender	Male = 1	1.229 **	0.568
Education	Formal = 1	1.420 ***	0.401
Age	Years	0.203	0.131
Age squared	Years	−0.002	0.001
HH size	Persons	0.020	0.115
Land tenure	Owner = 1	−0.440	0.534
LnNFI	Naira	0.051	0.040
Fertilizer use	Yes = 1	0.799 *	0.410
Irrigation	Yes = 1	1.593 ***	0.366
Credit	Yes = 1	0.217	0.458
Cooperative	Yes = 1	0.825 **	0.377

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Extension	Yes = 1	0.955 **	0.392
Constant		−7.841 ***	2.869
Observations	205		
Pseudo R^2	0.293		
Prob > χ^2	0.000		

Note: *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

4.3. Covariate Balance Before and After Matching

Table 4 compares mean values of covariates before and after Nearest Neighbour Matching and reports standardized percentage bias. Prior to matching, substantial imbalances existed between adopters and non-adopters across key covariates, including fertilizer use (% bias = 59.0, $p < 0.001$), irrigation (% bias = 89.0, $p < 0.001$), extension (% bias = 61.6, $p < 0.001$), and education (% bias = 60.0, $p < 0.001$). Such imbalances indicate the presence of significant selection bias and confirm the necessity of a matching procedure.

After matching, covariate balance improved markedly. The standardized bias for fertilizer use fell from 59.0% to 9.3% (84.3% reduction), for extension from 61.6% to 6.1% (90.0% reduction), and for irrigation from 89.0% to 25.7% (71.1% reduction). The Propensity Score Test (PSTEST) summary confirms this improvement: pseudo-R^2 dropped from 0.344 (pre-matching) to 0.098 (post-matching), and the LR chi-square became statistically insignificant ($p = 0.138$), indicating that observable covariates no longer jointly predict treatment status. Mean bias decreased from 41.0% to 16.5%, and median bias from 34.0% to 15.0%, values consistent with high-quality matching [19,18].

Table 4. Covariate balance before and after matching (Nearest Neighbour).

Variable	Sample	Treated Mean	Control Mean	% Bias	% Reduction	t-stat	p-value	V(T)/V(C)
Gender	U	0.794	0.643	34.0	—	2.44	0.015	.
	M	0.750	0.926	−39.6	16.5	−2.86	0.005	.
Education	U	0.514	0.235	60.0	—	4.27	0.000	.
	M	0.471	0.574	−22.1	63.1	−1.20	0.233	.
Age	U	44.71	38.05	57.9	—	4.14	0.000	0.94
	M	45.74	47.59	−16.1	72.2	−0.96	0.337	1.21
Fert_use	U	0.720	0.439	59.0	—	4.23	0.000	.
	M	0.765	0.721	9.3	84.3	0.58	0.560	.
Irrigation	U	0.673	0.265	89.0	—	6.36	0.000	.
	M	0.647	0.529	25.7	71.1	1.39	0.166	.
Cooperative	U	0.617	0.449	34.0	—	2.43	0.016	.
	M	0.588	0.529	11.9	65.0	0.69	0.493	.
Extension	U	0.673	0.378	61.6	—	4.41	0.000	.
	M	0.662	0.632	6.1	90.0	0.36	0.722	.

Note: U = Unmatched; M = Matched. V(T)/V(C) = variance ratio of treated to control.

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Table 5. PSTEST summary: Balance diagnostics before and after matching.

Sample	Ps R²	LR χ^2	$p > \chi^2$	MeanBias	MedBias	B	R	%Var
Unmatched	0.344	97.72	0.000	41.0	34.0	156.5*	0.61	0
Matched	0.098	18.55	0.138	16.5	15.0	77.1*	1.06	0

Note: * B > 25%; R outside [0.5; 2.0].

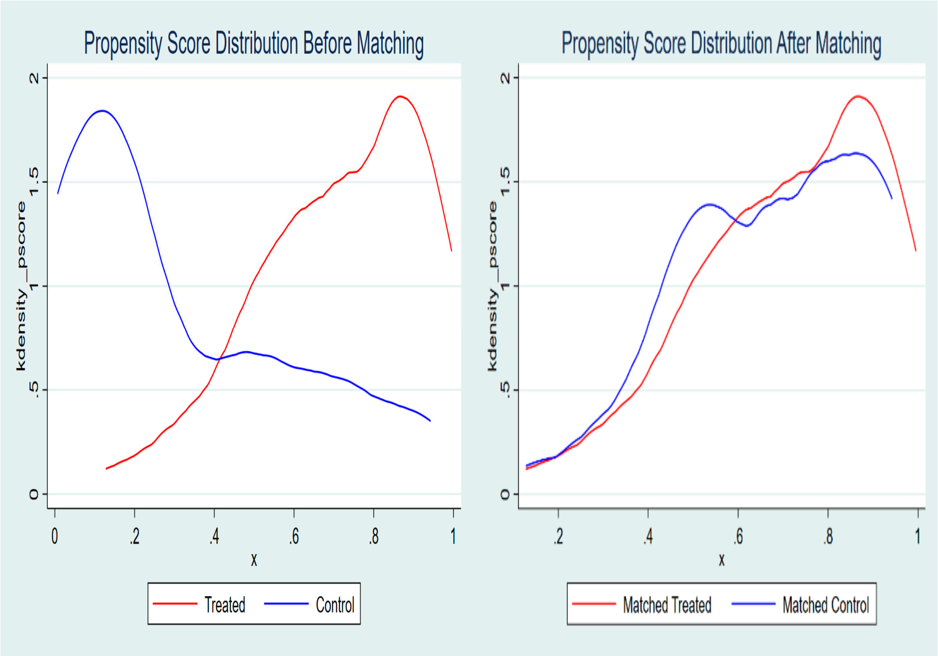

Figure 1. Distribution of Propensity Score Before and After Matching.

Figure 1 shows the distribution of propensity scores before and after nearest neighbour matching. Before matching, there is a clear distinction between treated and control groups, with limited overlap in the ends, showing potential selection bias and lack of comparability. After matching, the distributions of the matched treated and control groups overlap substantially across the propensity score range, suggesting that the matching procedure effectively improved the balance of observable characteristics and ensured common support. This indicates that the matched sample is suitable for estimating the treatment effect [19,18].

4.4. Average Treatment Effect on the Treated (ATET)

Table 6 presents the ATET estimates. In the unmatched comparison, adopters achieved an average log-yield of 8.172 compared to 7.757 for non-adopters, a raw difference of 0.414 log-units (t = 4.710, p < 0.01). However, this estimate includes selection bias due to pre-existing differences between groups.

After applying Nearest Neighbour Matching, the ATET is 0.399 log-units, significant at the 5% level (t = 2.590). This coefficient implies that adopting improved maize seed varieties leads to approximately a 49% increase in farm yield (exp (0.399) − 1 ≈ 0.49) compared to observationally similar non-adopters. The reduction in magnitude from the unmatched to the matched estimate (0.414 to 0.399) reflects the successful adjustment for selection bias, while the remaining effect represents the true causal contribution of improved seeds to farm productivity. These findings are consistent with prior evidence from Nigeria and across Sub-Saharan Africa documenting yield advantages of 40–50% for adopters [10].

Table 6. Average Treatment Effect on the Treated (ATET) for IMV adoption.

Sample	Treated	Controls	Difference	S.E.	t-stat
Unmatched	8.172	7.757	0.414	0.088	4.710 ***
Matched (ATET — Nearest Neighbour)	8.162	7.763	0.399	0.154	2.590 **

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively. Outcome variable is natural log of maize yield (kg/ha).

4.5. Robustness Checks

Table 7 presents results from alternative matching specifications. Under Radius Matching with a caliper of 0.01, the treatment effect ranges from 0.433 to 0.526 log-units (t = 3.13–3.41), significant at the 1% level. Radius Matching with calipers of 0.05 and 0.1 yield effects of 0.461 (t = 2.94) and 0.433 (t = 3.13), respectively. Kernel Matching produces an effect of 0.480 log-units (t = 3.010). The stability of results across these diverse matching algorithms provides strong evidence that the estimated yield benefits of IMV adoption are not sensitive to model specification and that the findings represent genuine causal effects rather than statistical artifacts.

Table 7. Robustness checks: ATET under alternative matching algorithms.

Matching Algorithm	Treated	Controls	Difference	S.E.	t-stat
Nearest Neighbour	8.162	7.763	0.399	0.154	2.590 **
Radius Caliper 0.01	8.172	7.638	0.526	0.154	3.410 ***
Radius Caliper 0.05	8.172	7.711	0.461	0.157	2.940 ***
Radius Caliper 0.1	8.172	7.738	0.433	0.138	3.130 ***
Kernel Matching	8.172	7.691	0.480	0.159	3.010 ***

Note: **, *** indicate significance at 5% and 1% levels, respectively.

5.

5.1. Interpretation of Key Findings

The findings of this study provide rigorous, micro-econometric evidence that IMV adoption significantly enhances maize productivity in Benue State, Nigeria. The PSM-estimated ATET of 0.399 log-units translates into an approximate 49% yield increase for adopters over observationally similar non-adopters. This magnitude is consistent with the broader African evidence base [2,10,20] and confirms the substantial productivity premium of improved genetic material under smallholder conditions.

The determinants of adoption follow expected patterns grounded in the Agricultural Household Model. The strong positive effects of irrigation access and fertilizer use highlight the non-separability of seed and input packages—a finding that reinforces previous evidence [12,13] and underscores the inadequacy of seed-only interventions. The significance of cooperative membership and extension contact points to the central role of institutional infrastructure in enabling technology transfer,

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consistent with prior evidence [2]. The gender gap in adoption, with male farmers being significantly more likely to adopt, echoes longstanding evidence on differential access to resources in Sub-Saharan Africa [5,6] and signals a need for targeted, gender-responsive interventions.

The insignificance of formal credit access, despite positive direction, may reflect structural weaknesses in rural financial markets, including small loan sizes, bureaucratic delays, and diversion of credit to non-farm uses, that prevent credit from serving as a binding adoption constraint. This is consistent with prior evidence [4] and suggests that liquidity-enhancing interventions must be paired with broader institutional reforms to be effective.

The robustness of the ATET across all matching specifications (Nearest Neighbour, Radius, Kernel) strengthens confidence in the causal interpretation of results. The overall findings align with the policy agenda for food security transformation in Nigeria and contribute localized, rigorous evidence to guide interventions in Benue State and structurally similar regions across Sub-Saharan Africa.

Table 8. Comparison with Existing Studies on Improved Maize Seed Variety Adoption.

Study	Data Source	Sample size	Method	Estimated Yield Increase	Key Contextual Differences
Olasehinde et al. (2023)	LSMS-ISA (National survey)	2,519 plots	Endogenous Treatment Effect + Metafrontier	38.7%	National sample; controls for unobserved heterogeneity; heterogeneous agro-ecological zones
Abdoulaye et al. (2018)	Multi-state household survey	~2,000 households	PSM + Instrumental Variable	~30%	Multi-state analysis; focuses on productivity and welfare outcomes
Kassie et al. (2011)	Uganda national survey	1,000+ households	PSM	40–50%	Focus on technology adoption and poverty reduction
Oyinbo et al. (2019)	Nigeria farm survey	Not specified	Production function / adoption model	Up to 70%	Focus on short-season maize varieties and climate adaptation
This study	Primary survey (Benue State)	205 farmers	PSM (NNM, Radius, Kernel)	49%	Benue-specific; primary data; high irrigation access and extension contact

Table 8 shows our estimated yield gain (49%) is higher than the 38.7% reported by Olasehinde et al. [11] using nationally representative data. Other factors may clarify this difference. First, this study focuses exclusively on Benue State, often referred to as the "Food Basket" of Nigeria, which has relatively favorable agro-climatic conditions and greater irrigation potential.

In our sample, approximately 67% of adopters had access to irrigation, which is substantially higher than the national average of less than 10%. Second, adopters in our sample also reported high levels of extension contact (67%) and cooperative membership (62%), both of which are known to enhance the effectiveness of improved agricultural technologies. Third, the use of primary survey data allows for more accurate measurement of farm-level input use and management practices compared to secondary national survey data. Fourth, methodological differences may also contribute to the variation in estimated impacts, as this study uses Propensity Score Matching on primary data, while Olasehinde et al. [11] employ an endogenous treatment-effect model on nationally representative data.

Importantly, our estimated yield increase of 49% falls within the range reported in previous studies [10,21]. This suggests that the productivity impact of improved maize varieties is highly context-dependent and may be higher in regions with better access to complementary inputs and infrastructure.

5.2. Policy Implications

The findings suggest that policies and subsidies should be implemented to increase IMV adoption rates, but seed provision alone is insufficient. The strong effect of irrigation access indicates that water security is a binding constraint. The insignificance of formal credit access, despite positive direction, may reflect structural weaknesses in rural financial markets [4]. The gender gap signals a need for targeted, gender-responsive interventions.

6. Conclusions

This study provides robust empirical evidence that the adoption of improved maize seed varieties significantly increases farm yield among smallholder farmers in Benue State, Nigeria. Using Propensity Score Matching on cross-sectional data from 205 farmers, the estimated ATET demonstrates that IMV adopters achieve approximately 49% higher maize yields than observationally comparable non-adopters. This yield advantage is consistent and statistically significant across alternative matching algorithms, confirming the causal contribution of improved genetic material to agricultural productivity.

The adoption decision is significantly driven by gender (male household heads), formal education, fertilizer use, irrigation access, cooperative membership, and extension contact. These findings underscore the importance of complementary inputs and institutional support as enabling conditions for technology uptake and highlight persistent gender gaps that require targeted policy attention.

Based on these findings, we recommend: (i) strengthening formal seed supply chains by expanding rural agro-dealer networks and enforcing quality control to reduce counterfeit or substandard seed circulation; (ii) promoting integrated input packages that combine improved seeds with fertilizer recommendations and water management support, backed by targeted subsidy schemes for resource-poor farmers; (iii) scaling up agricultural extension services with farmer field schools and digital communication tools to broaden reach in remote communities; (iv) supporting farmer cooperative capacity building as a platform for information sharing, collective input procurement, and group credit schemes; and (v) designing gender-responsive policies that specifically address women's access constraints to seeds, extension, and credit.

This study is subject to limitations. The cross-sectional design precludes full control of time-invariant unobserved heterogeneity; panel data would enable more rigorous identification. The findings are context-specific to Benue State and may not generalize to regions with different agroclimatic and institutional conditions without further validation. Future research should explore long-run adoption dynamics, profitability and cost-benefit analysis, and heterogeneous treatment effects by gender, farm size, and agroecological zone.

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