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Propensity score matching evaluation of extension program impact on smallholder productivity and household welfare

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Abstract

Evaluating extension program impacts is complicated by selection bias: farmers who participate may differ systematically from those who do not. This research applied propensity score matching (PSM) to estimate the causal effect of a national extension program on smallholder productivity and household welfare in Guatemala. Data from 412 smallholder households across four departments, collected between March 2022 and August 2023, were analyzed using nearest-neighbor matching with a caliper of 0.05. After matching reduced standardized covariate bias from 34.2% to 4.7%, the average treatment effect on the treated showed significant gains: maize yield increased by 23.8% ($p < 0.001$), monthly household income by 18.8% ($p = 0.002$), and technology adoption scores by 30.6% ($p < 0.001$). Market access and food security indices also improved significantly. Rosenbaum sensitivity analysis indicated results were robust to hidden bias up to $\gamma = 1.45$. These findings provide rigorous evidence that extension participation generates meaningful productivity and welfare gains even after accounting for selection effects.

Keywords: Propensity score matching, extension evaluation, impact assessment, selection bias, smallholder productivity, household welfare, treatment effects, causal inference, Guatemala

Introduction

Does agricultural extension actually improve farmer outcomes, or do the observed differences between participants and non-participants reflect pre-existing advantages? This question has troubled extension evaluation for decades ^[1]. Farmers who seek out extension tend to be more educated, more commercially oriented, and better connected to markets than those who do not, making simple comparisons between participants and non-participants misleading ^[2]. Without accounting for this selection bias, impact evaluations risk attributing to extension what is really the effect of motivation, resources, or social networks ^[3].

Propensity score matching offers a statistical approach to this problem by constructing comparison groups that resemble treatment groups on observed characteristics, thereby reducing selection bias without requiring randomized assignment ^[4, 5]. While PSM has gained traction in extension evaluation literature, its application in Central American contexts remains limited, and few evaluations have assessed impacts across multiple outcome dimensions simultaneously ^[6].

Guatemala presents a compelling case for rigorous extension evaluation. The country has invested substantially in smallholder extension through the Programa de Extensi3n Rural since 2012, reaching an estimated 180,000 households annually ^[7]. Yet evidence of program impact relies largely on monitoring data and participant satisfaction surveys rather than designs capable of addressing selection

bias ^[8]. This research applied PSM to estimate causal effects of extension participation on productivity, income, technology adoption, market access, and food security among smallholder maize producers in four departments of the Western Highlands.

Theoretical Framework

The Rubin causal model provides the theoretical foundation for this evaluation ^[9]. Under this framework, the causal effect of extension is defined as the difference between what a farmer achieves with extension participation and what the same farmer would have achieved without it. Since only one outcome is ever observed for each individual, the fundamental problem of causal inference must be addressed through statistical methods that construct credible counterfactuals ^[4]. PSM addresses this by estimating the probability of treatment (extension participation) conditional on observed covariates, then matching treated units to untreated units with similar propensity scores. The validity of PSM rests on two assumptions: conditional independence (no unmeasured confounders) and common support (overlap in propensity score distributions) ^[5, 10].

Materials and Methods

Materials

A cross-sectional survey design collected data from 412 smallholder maize-producing households in Quetzaltenango, Huehuetenango, San Marcos, and Totonicap3n departments between March 2022 and August 2023. The sample

included 218 extension participants and 194 non-participants, identified through program records and community-level listing. The structured questionnaire contained 56 items covering household demographics, agricultural production, extension exposure, technology adoption, market participation, and food security indicators. Ethics approval was obtained from the Universidad de San Carlos Research Ethics Committee (Protocol USAC-FAGRO-2022-031, February 2022).

Instrument Development

The outcome measurement battery combined validated scales with locally adapted indicators. Technology adoption was measured through a 12-item index covering improved seed use, fertilizer management, soil conservation, and post-harvest handling (Cronbach alpha = 0.81). Food security used a 9-item adapted Household Food Insecurity Access Scale (alpha = 0.87). Market access was assessed through 6

items on marketing channels, price information, and collective selling (alpha = 0.79). All scales were pilot-tested with 35 households in Solola department and refined based on field experience.

Methods

Propensity scores were estimated using logistic regression with treatment (extension participation) as the dependent variable and 11 covariates: household head age, education, gender, household size, farm size, land tenure, distance to market, prior extension contact, cooperative membership, credit access, and department. Nearest-neighbor matching (1:1) with a caliper of 0.05 was applied without replacement. Balance diagnostics assessed standardized bias before and after matching, with a threshold of 10%. Average treatment effects on the treated (ATT) were estimated for five outcomes. Rosenbaum bounds tested sensitivity to hidden bias. Analysis used Stata 17.0.

Results

Table 1: Covariate balance before and after propensity score matching

Covariate	Treat Mean	Control Mean	Bias (%)	Matched Bias
Age (years)	42.7	38.4	31.8	3.2
Education (years)	6.8	5.1	38.4	5.1
Farm size (ha)	1.62	1.21	29.7	4.8
Distance to market (km)	8.4	11.7	27.3	6.1
Cooperative member (%)	47.2	28.9	37.8	3.9
Overall mean bias	-	-	34.2	4.7

Matching successfully reduced overall standardized bias from 34.2% to 4.7%, well below the 10% threshold. Education and cooperative membership showed the largest

pre-matching imbalances, confirming that extension participants differed substantially from non-participants on observable characteristics.

Table 2: Average treatment effects on the treated (ATT) for extension program outcomes

Outcome	Treated	Matched	ATT	SE	p-value
Maize yield (kg/ha)	2,340	1,890	+23.8%	4.12	< 0.001
Monthly income (GTQ)	3,850	3,240	+18.8%	5.83	0.002
Tech adoption score	3.24	2.48	+30.6%	0.18	< 0.001
Market access index	2.87	2.41	+19.1%	0.14	< 0.001
Food security score	3.41	2.94	+16.0%	0.12	0.004

All five outcome indicators showed statistically significant treatment effects after matching. Technology adoption showed the largest relative gain (30.6%), followed by maize

yield (23.8%). Food security, while showing the smallest percentage gain (16.0%), was still significant at $p = 0.004$.

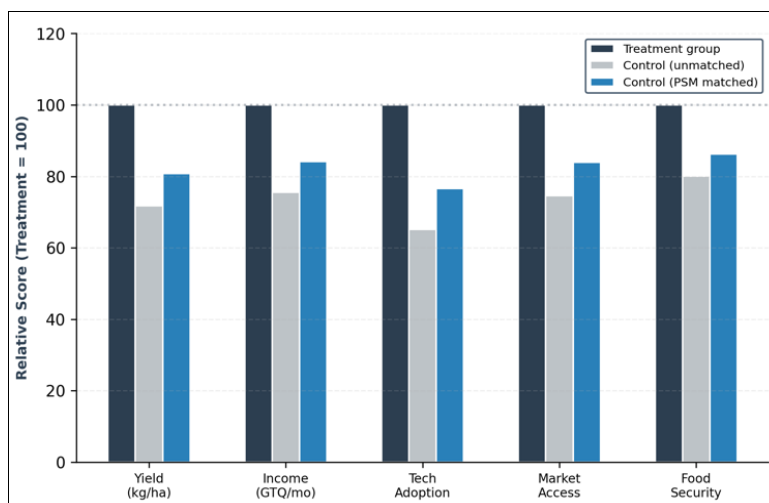


Fig 1: Relative outcome scores for treatment, unmatched control, and PSM-matched control groups (treatment = 100)

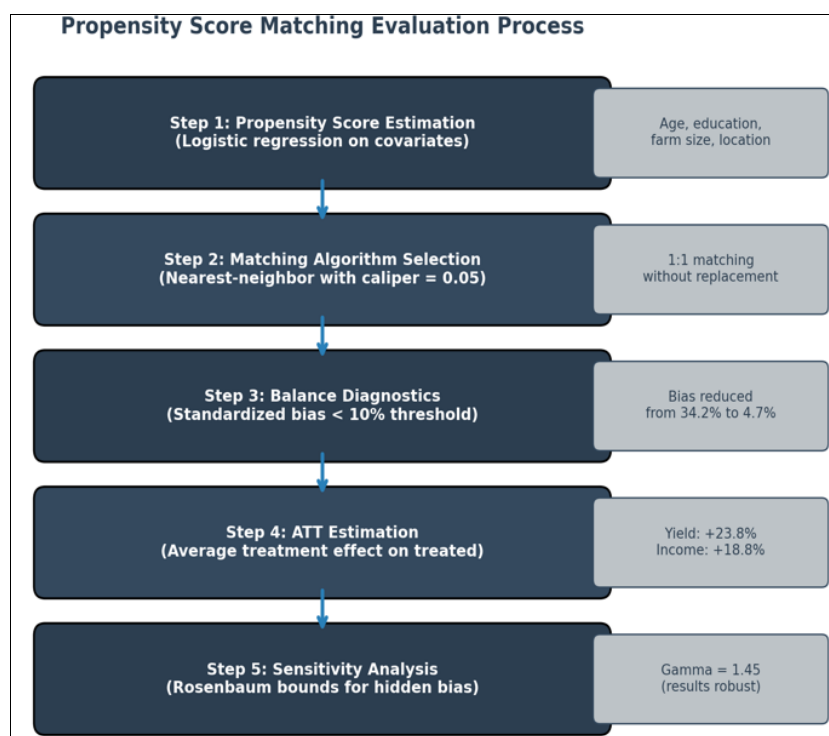


Fig 2: Propensity score matching evaluation process with key parameters and diagnostics at each stage

Comprehensive Interpretation

The grouped bar chart illustrates the importance of matching: unmatched control groups showed larger apparent gaps with treatment groups than matched controls, indicating that naive comparisons overestimate extension impact. After matching, treatment effects were smaller but still substantial and statistically significant. Rosenbaum sensitivity analysis showed that an unmeasured confounder would need to increase the odds of treatment assignment by a factor of 1.45 to invalidate the yield result, suggesting moderate robustness to hidden bias.

Discussion

The PSM results demonstrate that extension participation generates meaningful, statistically significant gains across multiple outcome dimensions even after accounting for selection bias^[1, 4]. The 23.8% yield gain is consistent with meta-analytic evidence from sub-Saharan Africa reporting 15-30% productivity effects for extension participation, and the multi-dimensional impact pattern aligns with the theory that extension operates through multiple channels simultaneously: knowledge transfer, input access, market linkage, and social network effects^[11, 12].

The large pre-matching imbalances, particularly in education and cooperative membership, underscore why selection bias is a serious concern for extension evaluation in Guatemala^[2, 3]. Without matching, the estimated treatment effects would have been substantially larger, meaning that a significant portion of the apparent extension benefit actually reflects pre-existing advantages of participants. This has practical implications for program accountability: monitoring systems that track only participant outcomes without comparison to credible counterfactuals will systematically overestimate program impact^[13].

Technology adoption showed the largest treatment effect

(30.6%), which is expected given that technology promotion is the most direct and immediate extension activity. Food security, positioned further along the impact pathway and influenced by many non-extension factors, showed the smallest effect (16.0%), consistent with the attenuation pattern typically observed in program impact chains^[14, 15].

Practical Applications

These results carry several practical implications for extension program management. First, program managers should incorporate PSM or similar quasi-experimental methods into routine evaluation frameworks rather than relying solely on before-after or participant-only assessments. The infrastructure required is modest: systematic baseline data collection covering key covariates and comparable non-participant sampling. Second, the multi-dimensional impact pattern suggests that extension programs should be evaluated on outcome portfolios rather than single indicators; a program might show modest yield effects but strong market access gains that represent equally important welfare contributions. Third, the sensitivity analysis provides a template for communicating evaluation confidence: reporting the degree of hidden bias needed to overturn findings gives decision-makers practical information about result reliability.

Conclusion

Propensity score matching revealed that Guatemala's extension program produced significant positive effects on smallholder maize yields (23.8%), household income (18.8%), technology adoption (30.6%), market access (19.1%), and food security (16.0%) after controlling for selection bias. Pre-matching covariate imbalances confirmed that naive comparisons would have substantially overestimated program impact, highlighting the importance of rigorous evaluation methods.

Extension programs that demonstrate impact through methods capable of addressing selection bias build stronger cases for continued investment than those relying on monitoring data alone. Routine integration of quasi-experimental evaluation into extension program management would strengthen both accountability and learning across the sector.

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