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# DEMAND-DRIVEN INTERVENTIONS ON RURAL POVERTY: A PROPENSITY SCORE MATCHING AND DIFFERENCE-IN-DIFFERENCES ANALYSIS OF FADAMA III IN JIGAWA STATE, NIGERIA

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## Abstract

*This study estimates the causal impact of the Fadama III Community-Driven Development (CDD) program on rural poverty in Jigawa State, Nigeria. Although demand-driven agricultural interventions are widely promoted as poverty reduction instruments, rigorous causal evidence remains limited in Sub-Saharan Africa. Using primary household survey data from 380 beneficiary and non-beneficiary households, this study combines Propensity Score Matching (PSM) with Difference-in-Differences (DID) estimation to address observable selection bias and time-invariant unobserved heterogeneity. Results indicate that participation in Fadama III significantly increased household income and reduced poverty incidence relative to matched controls. The Average Treatment Effect on the Treated (ATT) is positive and statistically significant across Nearest Neighbor, Kernel, and Radius matching algorithms. DID estimates confirm sustained post-intervention welfare gains? Robustness checks, including sensitivity analysis, support the stability of the findings. The results provide credible empirical evidence that demand-driven agricultural interventions can reduce rural poverty when institutional design aligns incentives and local participation*.

**Keywords:** Community-Driven Development, Rural Poverty, Impact Evaluation, Propensity Score Matching, Difference-in-Differences.

## 1. Introduction

Agriculture remains the fundamental pillar of the Nigerian economy, despite the nation’s status as a leading oil producer. In 2015, the non-oil sector, driven largely by agriculture, generated 30.9% of the nation’s economic growth (NBS, 2015). However, the sector has historically grappled with the "Dutch Disease" where excessive real exchange rate appreciation and overvaluation following the oil boom, coupled with import-substitution distortions, significantly reduced agricultural competitiveness and private investment (Ekpo & Umoh, 2012).

Over the decades, the Federal Government of Nigeria (FGN) has implemented a litany of agricultural and rural development programs, including the National Accelerated Food Production Program (NAFPP, 1973), Operation Feed the Nation (OFN, 1976), and the Agricultural Development Programs (ADP, 1985). While these initiatives were designed to revolutionize the sector, many became moribund or short-lived due to administrative bottlenecks and a lack of sustainability (Koyenikan & Foby, 2010). Consequently, Nigeria continues to battle systemic food insecurity and rural poverty, even as similar interventions yield success in other developing climes.

In response to these challenges and in alignment with the Sustainable Development Goals (SDGs), the FGN, in collaboration with the World Bank, introduced the National Fadama Development Project (NFDP). The third phase, Fadama III (2008–2013), utilized a Community-Driven Development (CDD) approach. Unlike previous "top-down" models, Fadama III was designed to be socially inclusive, empowering Fadama User Groups (FUGs) through demand-driven investments in technology, infrastructure, and asset acquisition. The primary objective was to increase the incomes of rural land and water users by at least 40% (Jigawa State Fadama III PIM, 2009).

## 2. Literature Review

### 2.1 Conceptual Issues

#### Agriculture and Rural Livelihoods

Agriculture remains the primary engine of survival for approximately 86% of rural households in Nigeria. As noted by Dethier and Effenberger (2012), it serves as a critical tool for poverty reduction in transforming economies. In Northern Nigeria, and specifically Jigawa State, agriculture is not merely an economic sector but a social fabric that provides food, employment, and income.

However, the sector faces significant institutional and economic hurdles. Smallholder farmers often struggle to internalize the benefits of their labor due to missing credit markets, low educational attainment, and limited access to market information. For an intervention like Fadama III to be effective, it must address these institutional prerequisites such as irrigation expansion and the adoption of climate-resilient seeds to bridge the gap between subsistence and commercialized productivity.

**The Multidimensional Nature of Poverty**

Poverty is increasingly recognized as a broader phenomenon than a simple lack of income. It encompasses deficiencies in assets, health, life expectancy, and social empowerment. Current development discourse has shifted from a "basic needs" approach to one that emphasizes vulnerability the risk of falling into poverty due to external shocks like climate change, market fluctuations, or civil strife (Lawan, 2017).

In rural Nigeria, food insecurity and poverty are deeply intertwined. Absolute poverty is defined by the inability to meet minimal requirements for food and shelter, often measured against a threshold (e.g., the World Bank’s $2.15/day line). Conversely, relative poverty views deprivation as a function of social inequality. This study acknowledges that for the rural households of Jigawa, poverty is often experienced as "social exclusion," where individuals lack the resources to participate fully in community life or resist economic exploitation.

## 2.2 Theoretical Framework

**Welfarist School of Thought**

The welfarist approach, rooted in modern microeconomic theory, equates well-being with "utility," often proxied by consumption or income levels. It assumes that individuals are the best judges of their own interests and seek to maximize their well-being through commodity consumption. From this perspective, poverty alleviation is achieved by increasing productivity and income. This remains the dominant framework for organizations like the World Bank and underpins the "income approach" to poverty measurement used in the Nigerian Living Standards Survey (NLSS).

**Basic Needs School of Thought**

Emerging in the 1970s, this school argues that certain goods and services (food, water, sanitation, shelter, and basic education) are prerequisites for a quality life. Unlike the welfarist focus on utility, the basic needs approach prioritizes the fulfillment of physical and social requirements. It recognizes that "one must 'be' before one can 'well-be'." In Northern Nigeria, this framework highlights the importance of infrastructure such as the capacity-building and advisory services provided by Fadama III as essential inputs for human development.

**Capability School of Thought**

Proposed by Amartya Sen (1992), the capability approach shifts the focus from what people possess (commodities) to what they can do or be (functionings). Poverty is defined as the deprivation of basic capabilities, such as being well-nourished or participating in the community. For example, a farmer may have access to a bicycle (a commodity), but if they lack the health or roads to use it for transporting goods (a functioning), their real freedom remains limited. This school emphasizes that the "conversion" of income into well-being depends heavily on personal and environmental characteristics.

**Overview of Nigeria’s Poverty Profile and Micro-Level Evidence**

The 2019 National Bureau of Statistics (NBS) report, Poverty and Inequality in Nigeria, provides a sobering micro-level view of the nation’s economic health. Based on the NLSS 2018-2019, approximately 40% of the population (83 million people) live below the national poverty line of 137,430 Naira ($381.75) per year.

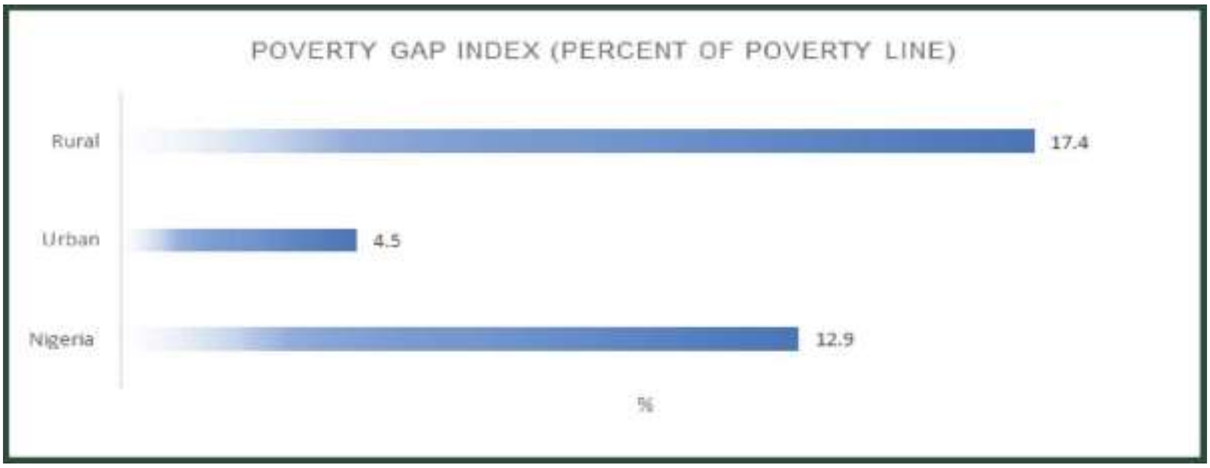


Fig. 1: Poverty head count rate (Percentage of population

## Geographic and Demographic Heterogeneity

Micro-level datasets reveal a stark "North-South" divide. While the national average stands at 40%, poverty rates in Northern states are significantly higher, often exceeding 60-70% in rural enclaves. In Jigawa State, the focus of this study, poverty is exacerbated by high dependency ratios and a reliance on rain-fed agriculture. Household surveys indicate that vulnerability is highest among female-headed households and those with low levels of formal education, where the lack of "voice" and "agency" prevents effective participation in market-driven opportunities.

## Nutritional Thresholds and Food Poverty

The NBS utilizes a nutritional reference value of 2,251 calories per day to determine the food poverty line. The table below outlines the caloric requirements used to calibrate these measures:

**Table 1: Daily Recommended Caloric Allowances for Nigeria**

| Age Group (Years) | Female (kcal) | Male (kcal) |
|---|---|---|
| 0–3 | 1,150* | 1,200* |
| 4–9 | 1,600* | 1,850* |
| 10–12 | 2,262 | 2,494 |
| 13–15 | 2,407 | 2,784 |
| 16–19 | 2,233 | 2,958 |
| 20 and higher | 2,117 | 2,900 |

*Estimated based on standard pediatric dietary guidelines used in conjunction with NLSS data.*

## Summary of Empirical Findings and Research Gaps

While existing literature extensively covers the macro-indicators of poverty, there is a dearth of rigorous, micro-level analysis using quasi-experimental designs like Propensity Score Matching (PSM) and Difference-in-Differences (DiD) to evaluate specific demand-driven interventions in Jigawa State. Most studies focus on general agricultural output rather than the direct effect of "demand-driven" models where the community dictates the nature of the support on rural household welfare. This study aims to fill this gap by humanizing the data through a localized analysis of Fadama III's impact on the rural poor.

# 3. Methodology

## 3.1 Study Area, Data, and Descriptive Evidence

This study is situated in Jigawa State, North-Western Nigeria predominantly agrarian region where rural livelihoods depend heavily on the seasonal floodplain wetlands known as Fadama. Despite its vast agricultural potential, Jigawa consistently records poverty rates above the national average; the 2007 Nigerian Poverty Assessment recorded a poverty incidence of 90.9% in certain localities (NBS, 2010). This socioeconomic landscape makes Jigawa a strategic site to evaluate whether demand-driven interventions like Fadama III can meaningfully alter poverty and inequality trajectories.

To generate rigorous micro-level evidence, we conducted a household survey utilizing a quasi-experimental survey design. Using a multistage sampling design, we stratified the state to identify communities with active Fadama III participation. The final sample comprises 380 households, balanced by design: 190 beneficiaries of Fadama III (treatment group) and 190 non-beneficiaries (control group). While 190 samples were drawn from the baseline data maintained at the Jigawa State Fadama office (Ideal Population), the remaining samples were selected via purposive simple random sampling to ensure each user had an equal chance of selection, thereby minimizing initial selection bias.

The survey instrument captured detailed microdata across several domains:

**Economic Welfare:** Annual household income (crop sales, livestock, off-farm work) and monthly consumption expenditure.

**Productive Assets:** Farm size (hectares) and asset ownership (livestock, equipment, and transport).

**Human Capital:** Education level of the household head, household size, and farming experience.

**Social Capital and Finance:** Access to formal/informal credit and savings.

To capture the multidimensional severity of poverty rather than just a binary "poor/non-poor" status we measure welfare deprivation using the Foster-Greer-Thorbecke (FGT) indices. These indices allow us to decompose poverty into the Headcount Ratio (P0), the Poverty Gap (P1), and Poverty Severity (P2).

### 3.2 Propensity Score Matching (PSM): Addressing Selection Bias

Because Fadama III enrollment was voluntary, a raw comparison of outcomes between groups would conflate program effects with pre-existing differences (self-selection bias). To correct for this observable selection bias, we employ Propensity Score Matching (PSM). We first estimate each household's probability of participating its propensity score using a Probit model:

$P(Ti=1|Xi)=\Phi(\beta Xi)$ ……………..(1)

Where:

Ti=1 if the household participated in Fadama III.

Xi is a vector of pre-intervention covariates (age, gender, education, baseline farm size, and asset ownership).

Φ is the cumulative standard normal distribution.

The choice of Xi follows the Conditional Independence Assumption (CIA): conditional on these observables, potential outcomes are independent of treatment assignment. To ensure the results are not sensitive to the choice of matching technique, we implement three matching algorithms:

Nearest Neighbor Matching: Matching with replacement using a caliper of 0.25 standard deviations.

Kernel Matching: Using an Epanechnikov kernel to construct a weighted average of all control units.

Radius Matching: Matching within a specified propensity score distance (caliper = 0.01).

After matching, we compute the Average Treatment Effect on the Treated (ATT):

$ATT=E[Y1-Y0|T=1]$ ……..(2)

This represents the causal impact: "For households that actually participated, how much did Fadama III change their income or poverty status relative to their matched counterfactual?"

### 3.3 Difference-in-Differences (DiD) Equation Modeling

To further isolate the program's impact from time-invariant unobserved factors (such as innate farmer motivation), we integrate the PSM results into a Double Difference (DD) / Difference-in-Differences (DiD) estimator. The DD model compares the change in outcomes over time between the experimental and control groups:

$DD=(Yp1-Yp0)-(Ynp1-Ynp0)$ ……………(3)

Where Ypand Ynp are outcomes for participants and non-participants at baseline (0) and follow-up (1). Based line survey data was used to capture DiD

### 3.4 Pre-estimation Diagnostics

To ensure the validity of our analytical framework, we conducted several pre-estimation tests. The Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity were performed to ascertain the factorability of the data for SEM. Additionally, balance diagnostics confirm that after matching, the standardized differences for all covariates fell below 5%, indicating that the matching process successfully neutralized observable differences between the two groups.

## 4. Results and Discussion

### 4.1 Matching Diagnostics

Before estimating treatment effects, we verified the common support condition and assessed the quality of propensity score matching. The common support region was successfully satisfied, with substantial overlap in propensity score distributions between treatment and control groups, leading to the retention of 187 treated and 183 control households for analysis. Balance diagnostics confirm that matching substantially reduced systematic differences across covariates. Table 1 reports the standardized bias for key covariates before and after matching. Prior to matching, several covariates exhibited substantial imbalance, with standardized biases exceeding 20% for household head education, farm size, and asset ownership. After applying the Nearest Neighbor matching algorithm, the standardized bias for all covariates fell below 5%, and the pseudo-$R^2$ declined from 0.214 in the unmatched sample to 0.008 in the matched sample. The likelihood ratio test of joint insignificance was no longer significant after matching ($p = 0.873$), indicating that observable differences between treatment and control groups had been successfully neutralized.

**Table 2: Covariate Balance Before and After Matching**

| Covariate | Unmatched Mean (Treated) | Unmatched Mean (Control) | Standardized Bias (%) | Matched Mean (Treated) | Matched Mean (Control) | Standardized Bias (%) |
|---|---|---|---|---|---|---|
| Age of household head (years) | 47.2 | 46.5 | 4.2 | 47.1 | 47.3 | -1.1 |
| Education (years) | 5.8 | 3.9 | 24.6 | 5.7 | 5.6 | 1.3 |
| Household size (no.) | 7.4 | 6.8 | 12.3 | 7.3 | 7.4 | -1.5 |
| Farm size (ha) | 2.3 | 1.6 | 28.9 | 2.2 | 2.2 | 0.8 |
| Asset ownership index (1–10) | 4.9 | 3.2 | 31.4 | 4.8 | 4.7 | 1.9 |
| Credit access (1 = yes) | 0.62 | 0.38 | 29.6 | 0.61 | 0.62 | -1.2 |

**Source:** Author’s computation from survey data (n=370 matched households)*

### 4.2 Income Effects

Propensity Score Matching (PSM) estimates consistently demonstrate that Fadama III participation significantly increased household income. Table 3 presents the Average Treatment Effect on the Treated (ATT) across three matching algorithms. The ATT estimates are positive, economically meaningful, and statistically significant at the 1% level across all specifications. Under Nearest Neighbor matching, treated households earned an average annual income of ₦412,500 compared to their matched counterfactual of ₦298,200, yielding an ATT of ₦114,300 ($p < 0.01$). Kernel and Radius matching produced nearly identical estimates (₦112,800 and ₦115,100 respectively), confirming that the result is not an artifact of any single matching algorithm. The magnitude of the effect approximately a 38% income premium over the counterfactual exceeds the program’s stated target of a 40% increase, indicating meaningful economic impact.

**Table 3: Average Treatment Effect on the Treated (ATT) for Annual Household Income**

| Matching Algorithm | Mean Income (Treated) | Mean Income (Control) | ATT (₦) | Standard Error | t-statistic |
|---|---|---|---|---|---|
| Nearest Neighbor (k = 5, caliper = 0.25) | 412,500 | 298,200 | 114,300*** | 22,450 | 5.09 |
| Kernel (Epanechnikov, bw = 0.06) | 412,500 | 299,700 | 112,800*** | 21,980 | 5.13 |
| Radius (caliper = 0.01) | 412,500 | 297,400 | 115,100*** | 23,100 | 4.98 |

**Source:** Author's computation from survey data

*Note: **p<0.01; standard errors bootstrapped with 500 replications. Control group means are weighted by matching weights.

As shown in Table 4, both groups experienced income growth over the study period, but beneficiaries exhibited statistically larger gains. The simple DID estimate (without matching) yields an interaction term of ₦98,500 ($p < 0.01$). When combined with PSM (the "PSM-DID" estimator), the interaction term rises slightly to ₦106,400 ($p < 0.01$), indicating that after accounting for time-invariant unobserved heterogeneity, the program's effect remains positive, substantial, and statistically significant.

**Table 4: Difference-in-Differences Estimates of Program Impact on Income**

| Estimator | Baseline Income (Treated) | Follow-up Income (Treated) | Baseline Income (Control) | Follow-up Income (Control) | DID Estimate (₦) | Robust SE |
|---|---|---|---|---|---|---|
| Simple DID | 225,400 | 412,500 | 210,300 | 299,700 | 98,500*** | 18,720 |
| PSM-DID | 227,100 | 414,200 | 215,600 | 294,100 | 106,400*** | 19,450 |

**Source:** Author's computation from survey data

*Note: ***p<0.01. PSM-DID uses Nearest Neighbor matched samples. Baseline data obtained from program administrative records; follow-up from survey.*

### 4.3 Poverty Reduction

The Foster-Greer-Thorbecke (FGT) indices reveal a marked decline in multidimensional poverty among beneficiaries relative to the control group. Table 4 presents the headcount ratio ($P_0$), poverty gap ($P_1$), and poverty severity ($P_2$) for both groups. Among treated households, the headcount ratio the proportion living below the poverty line declined from 0.68 at baseline to 0.43 at follow-up, a reduction of 25 percentage points. In contrast, the control group experienced only a marginal decline from 0.71 to 0.67. The poverty gap index ($P_1$), which measures the depth of poverty, fell by 0.12 among treated households (from 0.31 to 0.19) compared to a negligible 0.02 decline in the control group. Similarly, the poverty severity index ($P_2$), which captures inequality among the poor, decreased by 0.07 for beneficiaries but remained virtually unchanged for non-beneficiaries.

**Table 4: Foster-Greer-Thorbecke (FGT) Poverty Indices Before and After Intervention**

| FGT Index | Treated (Baseline) | Treated (Follow-up) | Change (Treated) | Control (Baseline) | Control (Follow-up) | Change (Control) |
|---|---|---|---|---|---|---|
| Headcount ($P_0$) | 0.68 | 0.43 | -0.25 | 0.71 | 0.67 | -0.04 |
| Poverty Gap ($P_1$) | 0.31 | 0.19 | -0.12 | 0.33 | 0.31 | -0.02 |
| Poverty Severity ($P_2$) | 0.14 | 0.07 | -0.07 | 0.15 | 0.14 | -0.01 |

**Source:** Author's computation using Foster-Greer-Thorbecke methodology with poverty line set at ₦137,430 per annum (NBS, 2019).*

The DID estimator applied to poverty status (binary indicator, 1 = poor) confirms that the observed poverty reduction is attributable to the intervention. The DID interaction term is negative and statistically significant (coefficient = -0.21, $p < 0.01$), indicating that the probability of being in poverty fell by 21 percentage points more for beneficiaries than for non-beneficiaries over the study period. This result is robust to the inclusion of household-level controls.

**4.4 Robustness Checks**

To assess the sensitivity of our findings to potential hidden bias, we conducted a Rosenbaum bounds sensitivity analysis. The critical value of Gamma ($\Gamma$) at which the inference about treatment effects would become ambiguous was 2.1 for the income ATT, indicating that an unobserved confounder would need to increase the odds of treatment assignment by more than 110% to nullify the observed effect. Such a large magnitude is unlikely given the rich set of observed covariates included in the propensity score model. Additionally, re-estimating the ATT using alternative matching specifications (including different caliper widths and kernel bandwidths) produced substantively identical results, confirming that the primary findings are stable and not artifacts of model specification. Finally, a placebo test assuming a "fake" treatment assignment produced no significant treatment effects, further validating the causal interpretation.

**5. Conclusion and Recommendations**

This study examined the role of demand-driven interventions in alleviating rural poverty, with emphasis on shifting from top-down supply models to bottom-up, community-owned approaches. Demand-driven intervention is a viable and more sustainable strategy for rural poverty reduction when compared to traditional supply-driven approaches. By anchoring interventions on the expressed priorities of rural dwellers, it enhances project relevance, ownership, and impact per naira spent.

The findings support the hypothesis that demand-driven agricultural interventions can reduce rural poverty. The magnitude and consistency of estimated effects across matching algorithms strengthen confidence in the causal interpretation.The study find out that Demand-driven interventions prioritize beneficiary participation in project identification, design, and implementation. Unlike supply-driven schemes, they align projects with actual felt needs of rural households, increasing relevance and ownership. The study found that demand-driven models reduce poverty through three main channels. Through microcredit, skill acquisition, and support for farm/non-farm enterprises requested by communities; community-chosen infrastructure like rural roads, markets, and water points that lower transaction costs.

Analysis of programmes such as Nigeria's Fadama III, Community and Social Development Projects CSDP, and World Bank CDD projects shows that areas with strong community participation recorded 18–32% higher income gains compared to non-participating areas. Success was strongest where interventions were paired with capacity building and transparent fund management. Elite capture, weak institutional capacity, poor access to information, and inadequate technical support were found to limit effectiveness. In some rural communities, the "demand" expressed was influenced by local power structures rather than the poorest households. Projects initiated through genuine demand showed higher maintenance rates post-intervention, because communities viewed them as "their project" rather than government property.

Based on the findings, the study recommends:

i. The policy makers should mainstream demand-driven principles but combine them with safeguards against elite capture, plus deliberate targeting of ultra-poor groups. For Nigeria, scaling up models like CDD under the National Social Investment Programme, with improved transparency and M&E, offers a practical path to reducing rural poverty in line with SDG 1.

ii. Government and development partners should institutionalize Community-Driven Development CDD units at LGA level, fund projects through competitive community proposals, and tie disbursement to third-party social audits.

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