



UNCONDITIONAL CASH TRANSFER AND AGRICULTURAL INPUT AND ASSETS USE; EVIDENCE FROM NIGERIAN HOUSEHOLD UPLIFTING PROGRAMME IN THE NORTH CENTRAL NIGERIA

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Abstract

The study evaluates the impact of Household Uplifting Programme (HUP) on vulnerable rural households' agricultural input and asset use in the North Central zone of Nigeria using a cross-sectional data on vulnerable rural HUP beneficiary households. The multi-Stage sampling was use to select 408 respondents comprising beneficiaries and non- beneficiaries from Benue and Nasarawa states. Applying the propensity Score Matching model, average treatment on the treated was estimated. The result showed that; being a beneficiary of the Household Uplifting Programme increased beneficiary's expenditure on agricultural input and asset use by 59 percent and this was significant at 1 percent.

Also, the socioeconomic characteristics showed that women were giving more preference in the program and it was meant for rural households. It is therefore recommended that Government should ensure that rural households in every part of the country is captured in the programme as its support for expenditure on agricultural inputs and assets provides the necessary capital needed for enhancing food security of the nation in general.

Key words: Cash transfer, agricultural inputs and assets use, Propensity Score Matching, Household Uplifting Programme (HUP)

1 Introduction

The Household Uplifting Programme (HUP) is a Cash Transfer programme and one of the four social investment programmes anchored by the Federal Government of Nigeria. It aims at responding to deficiencies in capacity and lack of investment in human capital of poor and vulnerable households. The Household Uplifting Programme commenced in September, 2016. The programme is designed to deliver timely and accessible cash transfers to vulnerable households and sets to support development objectives and priorities, to achieve specific outcomes such as household consumption, increased utilization of health and nutrition services,

school enrolment and attendance, environmental sanitation and asset acquisition and sustainable livelihood.

Cash transfer has become an important and effective policy tool for reducing household vulnerability in developing countries and is increasingly seen as an effective approach to tackling multi-dimensional poverty and vulnerability (Fiszbein *et.al.*, 2009). In Africa, conditional cash transfer has been implemented with success in so many developing countries like Kenya, Malawi, Ghana, Ethiopia and South Africa. In sub-Saharan Africa, about forty countries have adopted the unconditional cash transfer (UCT) (Bastagli *et al.*, 2016). In Nigeria, social protection policy and programming have emerged in recent years, with the government and its development partners currently implementing cash transfers to address the country's high rates of poverty and vulnerability (Overseas Development Institute, 2011).

The use of cash transfer depends on the how beneficiaries perceive these funds. Literature on intra-household allocation shows that households respond differently to income changes depending on who has the control of the resources within the households (Quisumbing, 2003). Agriculture is perceived to be a desirable economic activity which poor households are inclined to invest on. Therefore, increase in income as a result of cash transfer has the potential of increasing expenditure on agricultural inputs in a bid to increase agricultural productivity.

The theoretical case for cash transfer is based on income effect theory which states that change in consumption is based on income which implies that individuals will generally spend more if they experience an increase in income and may spend less if their income drops. It is also based on household decision making or intra household resource allocation with the assumption that individual can be trusted and empowered to make effective use of resources available to them (intra household resource allocation) to improve their living standards. Rural households in developing countries often face significant constraints in terms of income. Modest but regular and reliable flows of income from cash transfers help households to smooth consumption, enabling to sustain spending on food, school and healthcare in lean periods, without the need to sell assets or take on debt as a result of increase in their disposable income. Over time, transfer income can help households to build human capital, accumulate productive assets, and obtain access to credit on better terms (DFID, 2011).

- 1) The broad objective of this paper is to evaluate the impact of Household Uplifting Programme on vulnerable rural household expenditure on agricultural input and asset use.

Specifically; to describe the socio-economic characteristics of the vulnerable rural beneficiary households in the study area and secondly, analyze the impact of HUP on agricultural inputs and asset's expenditure of the vulnerable rural beneficiary households.

The following research questions were addressed:

- i) What are the socio-economic characteristics of vulnerable rural beneficiary households in the study area?
- ii) Does HUP have a significant impact on agricultural input and asset expenditure of vulnerable rural beneficiary households in the study area?

In recent years, there has been an increasing evidence of cash transfer impacts on agricultural inputs and assets expenditure for instance,

The Zambia's Child Grant Programme led to a 34 percent increase in the area of worked land as well as an increase in the use of agricultural inputs, including seeds, fertilizers and hired labour. The growth in input use led to an approximately 50 percent increase in the value of overall production, which was primarily sold rather than consumed on farm. The cash transfer produced an income multiplier at the households. Lesotho's Child Grant Programme increased crop input use and expenditures, including an eight-percentage point boost in the share of households using pesticides (from a base of 12 percent) (FAO, 2014).

Todd *et al.* (2010) and Gertler *et al.* (2012) found that the Mexican PROGRESA programme led to increased land use, livestock ownership, crop production, agricultural expenditures and a greater likelihood of operating a microenterprise.

Martinez (2004) found that the Bono Solidario (BONOSOL) pension programme in Bolivia had positive impacts on animal ownership, expenditures on farm inputs, and crop output, although the specific choice of investment differed according to the gender of the beneficiary.

Covarrubias *et al.* (2012) and Boone *et al.* (2013) found that the Malawi Social Cash Transfer Programme (SCTP) led to increased investment in agricultural assets, including crop implements and livestock and increased satisfaction of household consumption by own production.

Berhane *et al.* (2011) found that the Productive Safety Net Programme led to a significant improvement in food security status for those that had participated in the programme for 5 years versus those who only received 1 year of benefits. Moreover, those households that participated in the PNSP as well as the complementary programmes had significantly higher grain production and fertilizer use.

Overall, the household Uplifting programme impact on expenditure on agricultural input and asset has not been empirically investigated in Nigeria. This is why this study is compelling and also to reduce paucity of literature on cash transfer impacts on agricultural input and asset expenditure in Nigeria and globally.

Econometrics and Model Specification

2.1 Analytical Framework

There are different techniques in policy impact evaluation viz:

1. Randomization Control Trial (RCT)
2. Propensity score matching (PSM)
3. Double-difference (DD) methods
4. Instrumental variable (IV) methods
5. Regression discontinuity (RD) design and pipeline methods e.t.c.

These methods vary by their underlying assumptions regarding how to resolve selection bias in estimating the program treatment effect. One can be used or a combination of two depending on what one wants to achieve and the data available. The crux of any impact evaluation is to how get a valid counterfactual/ control group. However, in this context, Propensity Score Matching is considered best for this study because the study is using a cross sectional data and there is no baseline data.

Propensity Score Matching

PSM is a statistical matching technique that attempts to estimate the effect of treatment policy or other interventions by accounting for the covariates that predicts receiving the treatment. It constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics (Khandker *et al.*, 2010)

PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment T conditional on observed characteristics X , or the propensity score:

$$P(X) = \Pr(T = 1/X) \quad (1)$$

The estimated propensity scores, $\hat{p}(x)$, matched-pairs can be constructed on the basis of how close the scores are across the two samples using any of the matching algorithm. Two groups were identified: the HUP cash transfer beneficiaries (denoted $H_i = 1$ for household i) and non-beneficiaries ($H_i = 0$). HUP beneficiaries (the “treated” group) are matched to non-HUP beneficiary households (control group) on the basis of the propensity score, that is, the probability of being treated given observed characteristics as defined by Rosenbaum and Rubin (1983):

$$p(X_i) \equiv \Pr(H_i = 1|X_i) = E(H_i|X_i), \quad 0 < p(X_i) < 1 \quad (2)$$

- where X is a vector of pre-exposure control variables/covariates

The application of PSM involves these steps

Selection of Covariates

The choice of covariates to include in the model, was based on relevant literature on determinants of expenditure on farm inputs and assets. According to Garrido *et al.* (2014), selection of variables should involve those that are theoretically related to treatment & outcome.

Estimation of Propensity Score

The estimation of the propensity score model is an essential step of the process as the omission of key variables can bias the estimated treatment effect (Heckman and Todd, 1998; Dehejia and Wahba, 1999). Propensity Score used to Compare treated and comparison individuals who have similar “propensities” or likelihoods for receiving treatment, conditional on a set of several covariates or likelihood that any given individual would be in the treatment group, given a set of measured characteristics.

Two groups were identified: the HUP cash transfer beneficiaries (denoted $H_i = 1$ for household i) and non- beneficiaries ($H_i = 0$). HUP beneficiaries (the “treated” group) are matched to non-HUP beneficiary households (control group) on the basis of the propensity score, that is, the probability of being treated given observed characteristics as defined by Rosenbaum and Rubin (1983):

$$p(X_i) \equiv \Pr(H_i = 1|X_i) = E(H_i|X_i), \quad 0 < p(X_i) < 1 \quad (6)$$

- where X is a vector of pre-exposure control variables/covariates

Selection of Matching Methods

Once propensity scores are computed, matching method is selected to create a comparison group based on propensity score. Matching can be done using Nearest Neighbour with or without replacement, Radius Matching with caliper, Kernel Weighting and Inverse Probability of Treatment Weighting etc. According to Starks and Garrido (2014), there is no universal best method in matching, rather it involves choosing the method that has the best balance and still meets the analytic goal.

In this study, nearest neighbour with replacement, radius with 0.01 caliper and kernel matching according to Becker and Ichinno (2002) were used to estimate the average treatment effect on the treated (ATT)

Assessing Matching Quality

$$\hat{P}(X|T=1) = \hat{P}(X|T=0) \quad (9)$$

Here, the region of common support needs to be defined where distributions of the propensity score for treatment and comparison group overlap.

The common diagnostic tools for assessing matching quality are

- Standardized differences

- Graphs – Quantile-quantile plots – Plots of covariates in treated and comparison groups
- Ratios of variance

In this context, matching diagnostic tools applied here were the Ps graph, standardized bias by Rosenbaum and Rubin (1985) using Ps test with option both, to compare between matched and unmatched samples.

Assessing the Sensitivity of Estimates to Unobserved Heterogeneity

The last step in propensity score matching estimation is to perform a sensitivity analysis. The PSM is based on observable characteristics and not robust against 'hidden bias'. However, a hidden bias might arise if there are unobserved variables which affect assignment into treatment and the outcome variable simultaneously which abolish the CIA. The sensitivity analysis can be conducted using the bounding approach suggested by Rosenbaum (2002) or simulation-based sensitivity analysis for matching estimators (sensatt) by Ichino *et al.*, 2006. In this study, the simulation-based sensitivity analysis for matching estimators (sensatt) was used to assess how matching estimators were robust against the unobserved variables which may affect assignment into treatment.

3.0 Methodology

3.1 Research Design

The research design employed was a quasi-experimental design using a cross-sectional data on vulnerable households who were beneficiaries of the Household Uplifting Programme (HUP) and vulnerable households who were not part of the programme yet mined from the various State Cash transfer office and the National social register. A total number of 408 respondents comprising 204 beneficiaries and 204 non-beneficiaries were used to determine the programme impact.

3.2 Study Area

This study was conducted in North Central zone of Nigeria.

The North Central Nigeria consists of the six states namely Nasarawa, Benue, Plateau, Niger, Kogi Kwara and the Federal Capital Territory situated geographically in the middle belt region of the country. The zone spans from the west, around the confluence of the River Niger and the River Benue. It covers latitude 7° 00' - 11° 30' North of the equator and longitude 8° 00' - 11° 00'.

East of the Greenwich meridian (Oladimeji, 2015). The zone is bounded to Bauchi, Kaduna, Zamfara and Kebbi States to the north; Cross-River, Ebonyi, Enugu, Edo, Ondo, Ekiti, Osun and Oyo States to the south; Taraba State and Republic of Cameroon to the east and the Republic of Benin to the west. The zone has a land area of 296, 898 km² representing about 32 percent of the country's total land area (NBS, 2008) as in Tsue *et al.*, 2014. The major ethnic groups in this zone are the Gwari, Baruba, Bargana, Nupe, Tiv, Yoruba, Igala, Idoma, Angas and Birom. It enjoys the tropical continental climate characterized by wet and dry seasons. Wet season is synonymous to planting season since agriculture in the area is rain-fed. Mean annual rainfall ranges between 1,200mm and 1500mm while temperature is high almost throughout the year except during hamattan period which begins in November and lasts until February. The weather is cold and dry during the period coupled with hazy atmosphere and dust particles flowing around. The vegetation of the North Central Nigeria cut across the three savannah belts (Guinea, Sudan and Sahel) and this is one of the reasons why both roots and cereals cropping are very popular in these ecological zones. Agriculture is the major occupation of this zone and produces large quantities of yam, cassava, sweet potatoes, sorghum, maize, rice, cowpea, soybean, groundnut, onion and sugar-cane.

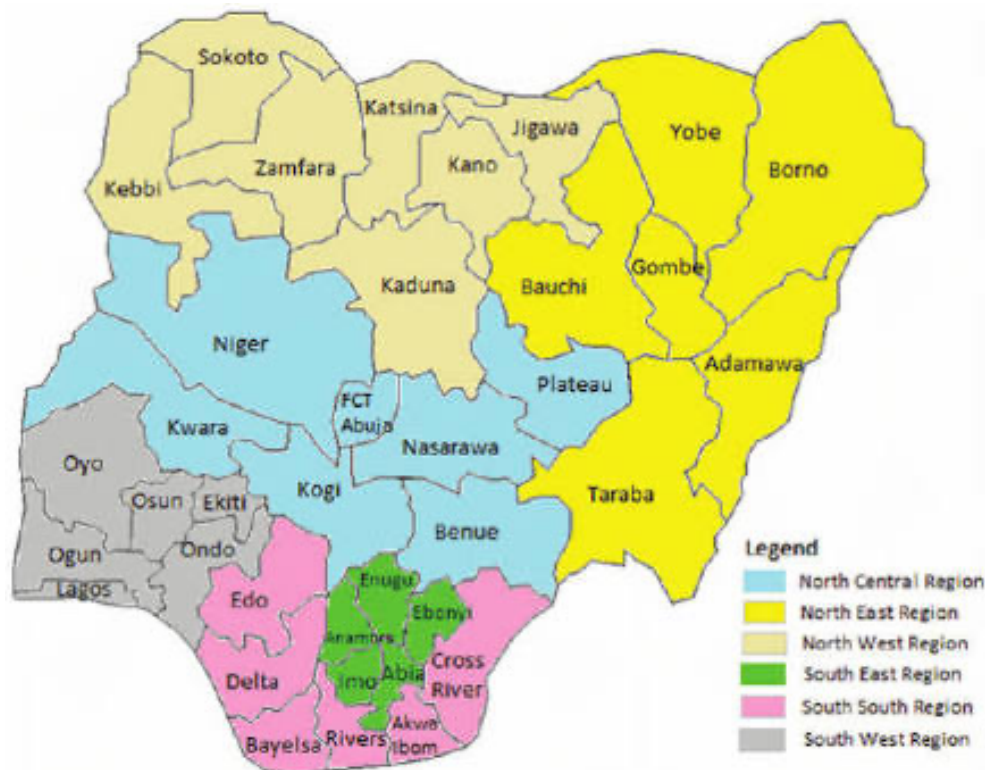


Figure1: Map of Nigeria showing the North Central States in Blue.

3.3 Population and Sampling Plan

The population for this study consists of HUP cash transfer beneficiary and non-beneficiary vulnerable rural households in Nasarawa and Benue States. The sample selection for the study was done in multi-stages. In the first stage, two states (Benue and Nasarawa) were purposively selected out of the six (6) states in the North Central. This is because the two states are among the poorest states in the north central and the federation (NBS report, 2010) and their situation is being worsened by herdsmen attack. According to Ikwuba (2011), Benue ranked the 8th poorest state in the federation. The study described its poverty as absolute, severe, widespread and multi-dimensional and has increased in the last decades. While the United Nations poverty index 2017 affirm that poverty rate in Nasarawa was about 52.4% in 2017. The second stage involved the selection of one Local Government from each of the three senatorial zones in each state based on the level of programme implementation which gave a total of six Local Government Areas. According to the State Cash transfer Office in both states, the programme is operational only in nine (9) and six (6) Local Government Areas of Benue and Nasarawa respectively. The population of the beneficiaries (24,660) and non-beneficiaries

(295,982) from the six selected Local Government Areas was mined from the State cash transfer Office data base and National Social Register respectively.

The sample size was determined using Taro Yamane (1973) formula

$$n = \frac{N}{1+N(e)^2} \quad (1)$$

where n is the sample size, N is the population and e is the level of precision or sampling error with 95% confidence interval.

Given N for the beneficiaries = **24,660**, e= 7%, $n = \frac{24660}{1+24660(0.07)^2}$ the sample size n for the beneficiaries was calculated as **204**. Also given N for non- beneficiaries as **295,982** and sample error of 7%, $n = \frac{295982}{1+295982(0.07)^2}$ the sample size n for the non -beneficiaries is **204**

Proportionate Stratified Random Sampling Formula was used to determine the sample size per the 9 LGAs selected in the two states. The formula was applied as follows:

Proportionate Stratified Random Sampling Formula: $n_h = (N_h / N) * n$ (2)

n_h = Sample size for h^{th} stratum= sample size per each LGA

N_h = Population size for h^{th} stratum= number of beneficiaries/non beneficiaries in each LGA

n = Size of entire sample=determined by Taro Yamane

N =Total population of beneficiaries/ non beneficiaries.

Using the above formula, the total sample size n for the two

groups were calculated as **408**

Table 1: Sample Selection

| State | Zones | LGA | Sampling frame | Sample size per LGA |
|-----------|-------|---------|---------------------|---------------------|
| Nassarawa | South | Lafia | Beneficiaries : | 51 |
| | | | Non-Beneficiaries : | 55 |
| | North | Akwanga | Beneficiaries : | 28 |
| | | | Non-beneficiaries : | 25 |

| | | | | | |
|-------|---------|-----------|---------------------|--------|----|
| | West | Kokona | Beneficiaries : | 4,317 | 36 |
| | | | Non-beneficiaries : | 73,568 | 51 |
| Benue | North | Vandeikya | Beneficiaries : | 5,270 | 43 |
| | | | Non beneficiaries : | 2714 | 2 |
| | Central | Buruku | Beneficiaries : | 2,923 | 24 |
| | | | Non-beneficiaries : | 68230 | 47 |
| | South | Oju | Beneficiaries : | 2,636 | 22 |
| | | | Non beneficiaries : | 35,169 | 24 |

Total Beneficiaries 24,660

Total Non-beneficiaries 295,982

Total Sample size 408

Source: Author's Computation

3.4 Sampling Technique

Data for the study were analyzed using descriptive and inferential statistics. Objective 1 was analyzed using descriptive statistics such as frequencies, percentages and mean etc, Objective 2 was achieved using Propensity Score Matching (PSM) to match beneficiaries and non-beneficiaries to ensure statistical equivalence between the groups after calculating expenditure on farm inputs such as fertilizers, hoes, cutlasses, seedlings, herbicides and pesticides for 2 consecutive years after the commencement of the programme. Then the average treatment on the treated (ATT) on total expenditure on farm inputs (two years) were estimated using nearest neighbour matching (one to one) with replacement but for robustness, alternative matching estimators such as radius with caliper 0.01 and kernel matching methods were also used

3.5 Model /Variable Specification

Measurement of Variables

- i. **Age** in years
- ii **Gender of household head:** Male headed households or female headed households;
1=male and 0=female
- iii **Household monthly income** in Naira
- iv **Occupation:** farming =1, Petty trading =2 and Others =3
- v **Land size:** measured in hectares
- Vi **Cash transfer:** H=1 or 0 otherwise
- Vii **Expenditure on Agricultural Inputs:** Expenditure on inputs was measured in Naira for 2yrs
- Viii. HUP: measured as dummy equals =1 if respondent is a beneficiary of HUP, 0 otherwise.

Model Specification

The propensity score was estimated was given that the treatment is binary using a logit model given as

$$p(X_i) = E(H_i|X_i) = \frac{1}{1+e^{-\beta X_i}} = \frac{e^{\beta X_i}}{1+e^{\beta X_i}} \quad (7)$$

where H= treatment indicator which is a binary variable coded as 1 if a household is a beneficiary of HUP and 0 otherwise.

X = is a set of covariates that determines participation namely: Occupation, Income, Land size, Gender of household head,

β = a vector of coefficients to be estimated.

Average Treatment effects on the Treated (ATT), τ is given as:

$$\tau \equiv E[E\{Y_{1i}|H_i = 1, p(X_i)\} - E\{Y_{0i}|H_i = 0, p(X_i)\}|H_i = 1] \quad (8)$$

where H is the index of exposure to treatment (i.e HUP) =1 or 0 otherwise. Y_{1i} and Y_{0i} are the potential outcome (expenditure on agricultural inputs and assets) in the two counterfactual situations of treatment (HUP beneficiary) and non-treatment (non- HUP beneficiary).

RESULTS AND DISCUSSION

4.1 Socio-economic Characteristics of Vulnerable Rural Beneficiary Households

The result of the socio-economic characteristics of the vulnerable households is shown in Table 2. The result shows that a total of 408 respondents were surveyed which comprises of 204 beneficiaries and 204 non beneficiaries. Out of the 204 beneficiary respondents, 23 percent were male while 77 percent were female which is an indication that women were given preference in the Household Uplifting Programme probably because they are more vulnerable. Mean age was 42 years while the minimum and maximum age of the respondent were 19 years and 90 years respectively. A total of 150 respondents were married which represent 74 percent of the household surveyed while 21 percent were widows (42 respondents) and 6 percent (12 respondents) were widowers which is evident that the programme is targeted at households. 77 percent of the households were farmers, 20 percent were petty traders and 3 percent had fishing as their occupation. This shows that the programme was designed for rural households and farming is their major occupation. The respondents had a mean household size of seven (7), with minimum household size of 1 and maximum of 21 persons. More than 50 percent of the respondents had between 6-10 household size. The large number of the household size is evident of the impact of the Fulani herdsmen on the households as they try to accommodate their extended family members especially in Benue state. This may have implication on their welfare outcomes. With respect to their educational backgrounds, 25 percent of the respondents had no education at all, 31 had primary education, 35 percent had secondary education and 0.98 tertiary education among the beneficiaries. This means that about 56 percent of the respondents falls between 0- 6 years of education which could under-pin why they are more vulnerable. The mean land size per hectare is 4.5 hectares, minimum is 0.5 ha and maximum were 12. This an indication that the respondents were majorly farming households. The mean income is ₦8625 with a minimum of ₦6500 and maximum of ₦12000.

Table 2: Distribution of Socio-Economic Characteristics of Respondents (n=204)

| Variable | Frequency | Percentage | Mean | Min | Max |
|----------------------------|------------------|-------------------|-------------|--------------|--------------|
| Age(yrs) | | | 42 | 17 | 90 |
| <20 years | 2 | 0.98 | | | |
| 21-25 | 11 | 5.39 | | | |
| 26-30 | 24 | 11.77 | | | |
| 31-35 | 28 | 13.72 | | | |
| 36-40 | 41 | 20.1 | | | |
| 41-45 | 26 | 12.75 | | | |
| 46-50 | 30 | 14.7 | | | |
| 51 and above | 42 | 20.59 | | | |
| Gender | | | | | |
| Male | 47 | 23.04 | | | |
| Female | 157 | 76.96 | | | |
| Marital Status | | | | | |
| Married | 150 | 74 | | | |
| Widows | 42 | 21 | | | |
| Widowers | 12 | 5 | | | |
| Single | 0 | 0 | | | |
| Occupation | | | | | |
| Farming | 157 | 77.83 | | | |
| Petty trading | 40 | 19.7 | | | |
| Fishing | 6 | 2.95 | | | |
| Household size | | | 7 | 1 | 21 |
| 1-5 | 70 | 34.31 | | | |
| 6-10 | 103 | 50.48 | | | |
| 11-15 | 21 | 10.29 | | | |
| 16-21 | 10 | 4.9 | | | |
| Education | | | | | |
| No formal education | 50 | 24.63 | | | |
| 0-6years | 63 | 31.03 | | | |
| 7-12years | 73 | 35.40 | | | |
| 13-15yrs | 18 | 8.86 | | | |
| Land size | | | 5 | 0.5 | 12 |
| 0-5 | 133 | 65.18 | | | |
| 6-10 | 70 | 34.3 | | | |
| 11-15 | 1 | 0.49 | | | |
| 16 and above | 0 | | | | |
| Monthly Income | | | | 8,652 | 6,500 |
| 12,000 | | | | | |
| 5-9 | 180 | 88.28 | | | |
| 10-14 | 24 | 11.76 | | | |
| 15 and above | 0 | 0 | | | |

Source: Author's Computation from Field Survey Data, 2020

4.2 Preliminary Analysis of the Goodness of Fit and Balance Diagnostics of Propensity Score Matching

An incorrectly specified propensity score model may lead to residual confounding bias; therefore, it is essential to use diagnostics to assess the propensity scores in a propensity score analysis.

4.2.1 Estimates of the propensity score and matching quality

The kernel density distributions of the propensity scores for the expenditure on agricultural inputs and assets outcome are shown in Figures 2 and 3 while Table 3 presents the summary of the PS test showing balancing of the covariates. A total number of 408 respondents were surveyed, comprising of 204 as beneficiaries (treated) and 204 non-beneficiaries (control). The covariates used for matching were monthly income, land size, gender of household head, age of respondent and occupation. The outcome variable was total expenditure on agricultural input within 2 years of the programme on inputs such as fertilizers, hoes, cutlasses, seedlings and pesticides while the treatment variable was cash transfer. On the basis of estimation of propensity score, 204 beneficiaries (treated) were matched and 171 non beneficiary (control) households. Applying logistic regression, the range of common support was selected to be [.065, .997], final block was 7 and the balancing property was satisfied.

The PS test was carried out to assess the balancing quality between the covariates before and after matching and the result is presented in Table 3. According to Diez *et.al* (2009) there should be no significant differences in the distribution of covariates between the beneficiaries and non-beneficiaries. The result shows a significant reduction of the pseudo- R^2 between matched and unmatched sample. Rubin (2001) recommends that R (that is, the ratio of treated to non-treated variances of propensity score) be between 0.5 and 2 for the samples to be considered sufficiently balanced. The Rubin's R is within range and supports the balancing of covariates between the groups. The insignificant LR χ^2 after matching supported the hypothesis that both

groups have the same distribution in covariates after matching ie the matched CT beneficiaries and non-beneficiaries are statistically not different from each other. The mean bias and median bias show a reduction between the matched group and unmatched group. Also, the percentage variance showed a significant reduction from 70 to 50 percent. in the food consumption model, which is also robust to the outcome variables.

Table 3: Summary of PS test showing Balancing of Covariates

| Sample | Pseudo R^2 | LRchi ² | P>chi ² | Mean Bias | Median Bias | B | R | %Variance |
|----------------|--------------|--------------------|--------------------|-------------|-------------|--------|------|-----------|
| Unmatched(exp) | 0.282 | 159.3 | 0.000 | 47.3 | 40.9 | 140.4* | 0.73 | 50 |
| Matched(exp) | 0.039 | 22.05 | 0.000 | 17.5 | 13.3 | 47.0* | 0.68 | 70 |

*if B>25%, and R outside [0.5;2}

Note: No. of Selected Blocks: EXP = 7

B= absolute standardized difference of means of the linear index of propensity in the matched and unmatched group

R= the ratio of treated to non-treated variances of propensity index (0.5 and 2)

Source: Author's Computation from Field Survey Data, 2020

The PS graphs which show the overlap of the distribution of the propensity scores across cash transfer beneficiaries and non-beneficiary groups for expenditure on agricultural input and assets outcome is displayed in Figures (3) and indicates the extent of overlap to be satisfactory. The histogram showing the percentage bias across the covariates for expenditure on agricultural inputs and assets outcome is displayed in Figure 4 and indicates the level of bias reduction in the matched and unmatched groups. Overall, the matching analysis shows that the balancing property is satisfied and hence confirms the matching quality of the propensity score matching model estimated.

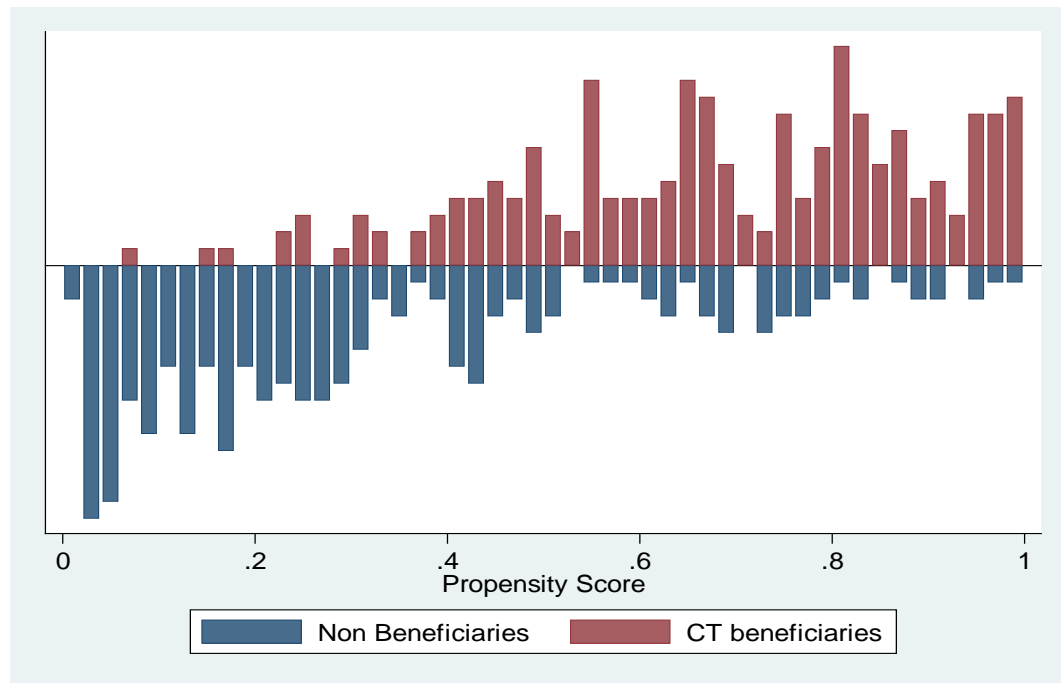


Figure 2: The Distribution of Propensity Scores between the Treated and Untreated for Expenditure on Farm Input

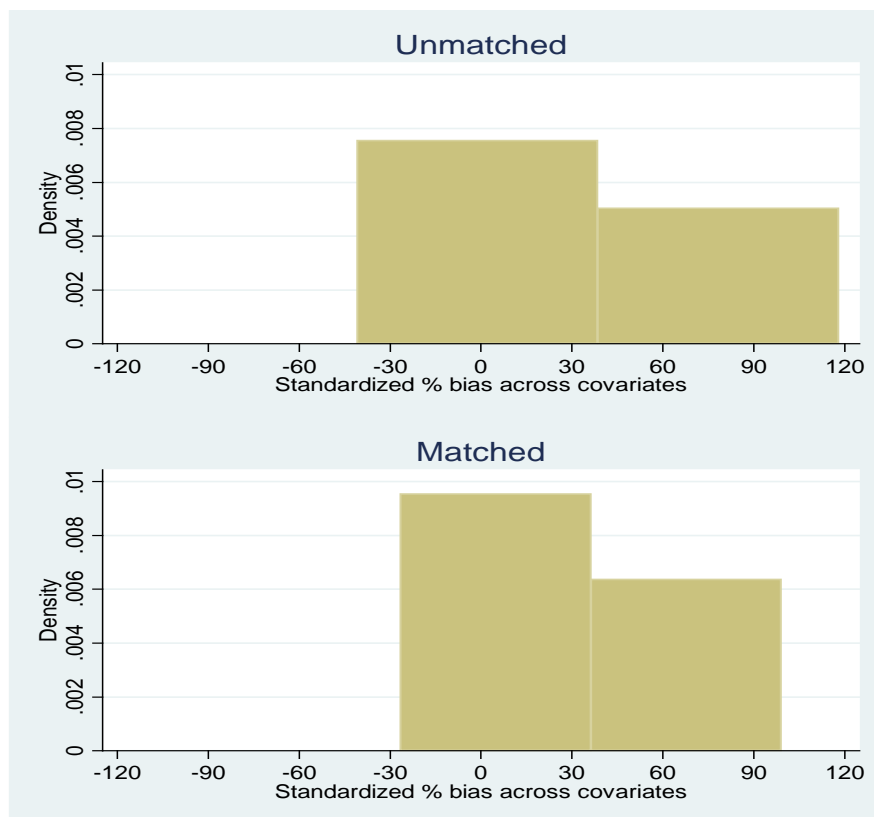


Figure 3: The Standardized Percentage Bias across Covariates for EXP

4.5 Impact of HUP on Expenditure on Agricultural Input The result of the estimates of average treatment on the treated (ATT) is presented in Table 5. The covariates used for matching were monthly income, land size, gender of household head, age of respondent and occupation. The outcome variable was total expenditure on agricultural input within 2 years of the programme on inputs such as fertilizers, hoes, cutlasses, seedlings, herbicides and pesticides while the treatment variable was cash transfer. On the basis of estimation of propensity score, 204 beneficiaries (treated) were matched and 171 non beneficiary (control) households. Applying logistic regression, the range of common support was selected to be [.065, .997], final block was 7 and the balancing property was satisfied. Matching was done using radius (Attr) with caliper 0.1, nearest neighbour and kernel methods for robustness to estimates. The result of the Attr was 0.595 with $t=10.0$ while $Attr_k=0.588$ with $t=8.78$. The average treatment on the treated (att) were positive and about the same magnitude. This implies that being a HUP cash transfer beneficiary increases the expenditure on agricultural inputs at about 59 percent and it is also statistically significant at 1 percent. This result leads to rejection of the null hypothesis that states that there is no significant impact of HUP on agricultural input expenditure of vulnerable rural beneficiary households in the Northcentral Nigeria. This outcome is possible because cash transfer can have an income multiplier effect on the households through investment in livelihoods that can increase income (Bailey, 2013). Expenditure on agricultural inputs may be considered as one of such income generating investments. The result is consistent with Daidone *et al.* (2019) who examined the household and individual-level economic impacts of cash transfer programmes in sub-Saharan Africa. Their findings showed that cash transfer had a statistically significant impact on agricultural production, agricultural inputs and assets. Also, the result is supported by FAO (2014) who investigated the Zambia's Child Grant Programme. Their analysis showed that cash transfer programme led to a 34 percent increase in the area of worked

land as well as an increase in the use of agricultural inputs, including seeds, fertilizers and hired labour. The Lesotho's Child Grant Programme increased crop input use and expenditures, including an eight-percentage point boost in the share of households using pesticides (from a base of 12 percent). See also Todd *et al.* (2010), Gertler *et al.* (2012), Martinez (2004) and Boone *et al.* (2013).

Table 4: ATT estimates of the Impact on Expenditure on Agricultural Inputs

| Methods | n. treat. | n. contr. | ATT | Std.Err. | T | B/strapping | Std.Err. | T |
|---------|-----------|-----------|-------|----------|------|-------------|----------|------|
| Attr | 204 | 171 | 0.59 | 0.04 | 12.0 | 0.59*** | 0.05 | 10.0 |
| Attk | 204 | 171 | 0.588 | - | - | 0.588*** | 0.06 | 8.78 |
| Attnd | 204 | 67 | 0.67 | 0.08 | 7.68 | 0.67*** | 0.07 | 9.18 |

*** indicates significance at 1 percent

Source: Author's Computation from Field Survey Data, 2020

4.6 Sensitivity analysis of unobserved heterogeneity

The simulation result of the ATT(s) is displayed in Table 4. The simulation was done using a simulation-based sensitivity analysis (Sensatt) consistent with Ichino *et al.*, (2006) to check for the presence of unobserved variables affecting both selection into treatment and outcome variable simultaneously. The ATT(s) were simulated with a cofounder U. It showed that the outcome and selection effect were positive and greater than 1 and there was no

difference between the baseline ATT and the simulated ATT. According to Nannicini (2007),

| | Att Baseline | Att simulated | Standard error | Outcome effect | Selection effect |
|------------|---------------------|----------------------|-----------------------|-----------------------|-------------------------|
| EXP | 0.67 | 0.67 | 0.08 | 1.95 | 1.02 |

both the outcome and selection effects must be positive and greater than one. This implies that the impact estimates of ATT are

insensitive to unobserved selection bias and are a pure effect of cash transfer beneficiary and the results estimated support and strengthen the robustness of the matching analysis above.

Table 5: The Sensitivity Analysis Result

Source: Author's Computation from Field Survey Data, 2020

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study examines the impact of unconditional cash transfer on household expenditure on farm inputs and assets in the North Central- evidence from Household Uplifting Programme (HUP) in Nigeria using propensity matching score (PSM) to create counterfactual group from the control group based on observed characteristics. Based on the findings, it therefore concluded that participation in HUP impacted positively and significantly on expenditure on Agricultural inputs and assets of the beneficiary households in the North Central Nigeria which is capable of reducing hunger and enhancing food security of these households.

5.3 Recommendations

Cash transfers whether conditional or unconditional have been proved to be effective tool in reducing poverty and vulnerability and the case of Household Uplifting Programme in Northcentral Nigeria is not different having been statistically tested. It is evident from this research that Government public interventions such as HUP which aims at responding to deficiencies in human capital of the poor and vulnerable households by delivering timely and accessible cash transfers to beneficiaries have significant positive impact on the beneficiary's expenditure on agricultural inputs and assets. It therefore recommended that;

- 1) Government should ensure that rural households in every part of the country is captured in the programme as its support for expenditure on agricultural inputs is capable of providing the necessary capital needed to reduce hunger and enhance food security of the nation in general.

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