Impact of Nutrition-Sensitive Agriculture on Rural Women Welfare: A quasi-experimental design

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Article History: Received: 30 June 2023; Revised: 04 September 2023; Accepted: 02 October 2023

Abstract

Women's welfare, defined as a state of being happy, healthy and prosperous which can be measured in terms of food and non-food consumption, is a top development target in Ethiopia. Various initiatives are being carried out to promote women's welfare, including nutrition-sensitive agriculture (NSA) interventions. The nutrition-sensitive agriculture interventions are being undertaken in the country's most vulnerable area. The study examined the impact of NSA interventions on the welfare of rural women. A multi-stage sampling technique was employed to select 94 participant and 166 non-participant women, for a total of 260 representative households. The study employed descriptive statistics as well as the propensity score matching (PSM) approach to attain its stated objective. The study's findings indicated that the intervention had a significant and positive influence on women's welfare. Thus, the sustained and wider dissemination of the nutrition-sensitive agricultural intervention would require building the capacity of key actors and institutionalizing the scheme in the regular, publicly supported extension program.

Key words: welfare, impact, nutrition sensitive agriculture and PSM
JEL Classification: D60

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1. Introduction

Women are the primary providers of home welfare in rural communities via nutrition and dietary improvement (K. Smith, 2017). Women's welfare can be improved when they engage in on-farm activities, notably backyard horticulture crop cultivation and small stock (chicken) raising. However, programs for productive development and the delivery of extension services usually ignore them. The poor social position of women, which is a result of ingrained cultural restrictions, might make morbidity and problems with food intake worse (Lange, Gherissi, Chou, Say, & Filippi, 2019). According to Quisumbing (2020), if men and women had equivalent social standing, the under-three child underweight rate would fall by almost 13%. Numerous programs for women's empowerment aim to reduce socio-cultural barriers and lessen their detrimental effects on women household's welfare. Such efforts have a variety of effects on rural women's families, including greater access to nutritious food.

It is really concerning to see how many people nationwide lack access to adequate food and nourishment, especially women and children. In Ethiopia, more than 38%, 23%, and 9% of children under five are stunted, underweight, or wasted, respectively (CSA, 2020). The percentage of undernourished women among women of reproductive age was 22 percent (Biswas, Rahman, Khanam, Baqui, & Ahmed, 2019). To improve the wellbeing of rural women, the Ethiopian government is collaborating with a number of non-governmental organizations (NGOs). The government's goal is to improve the nutritional condition of those who lack access to food, particularly small children and mothers who are capable of carrying children. Feed the Future Ethiopia is a five-year flagship multi-sector nutrition intervention effort financed by USAID (Idd, 2017).

Development partners are pushing nutrition-sensitive agriculture (NSA) solutions to address the problems associated with malnutrition (Di Prima, Wright, Sharma, Syurina, & Broerse, 2022). In order to combat malnutrition and a lack of micronutrients, nutrition-sensitive agriculture (NSA) strives to provide a variety of food sources that are nutritionally dense and rich (Junuthula, Kumari, & Srinivasan, 2022). NSA is a widely used strategy that allows for a lot of adaptability to match certain biophysical and sociocultural circumstances. Improved nutrition for the poor is a goal of the NSA, particularly for mothers and small children. Food for people living throughout the world can be made affordable and accessible, diversified and sustainable, and nutrient-dense through NSA-based agricultural production (Junuthula, Kumari, & Srinivasan, 2023).

However, very little has been done to provide evidence that shows how NSA intervention affects welfare outcomes and the difficulties encountered. In Ethiopia, nutritionally sensitive agriculture is a relatively recent phenomenon that has not received much in-depth study. NSA intervention may help to lower welfare insecurity since it enables households to enhance their standard of living. Some empirical studies have been carried out by various scholars to assess the impact of NSA in Ethiopia. Mucheye (2021) investigated the impact of nutrition-sensitive agriculture on women's empowerment. Gizachew (2019) studied the influence of NSA intervention on income outcomes in a similar way. These empirical studies, however, concentrated on certain regions and variables, such as income and empowerment, which didn't reflect the welfare of rural women and on the traditional impact assessment procedures. Therefore, this study uses propensity score matching (PSM) to examine the impact of NSA intervention on the welfare of rural women. It also addresses the issue caused by quasi-experimental designs in agricultural research and development activities. Households who participate in the program may differ from non-participants in a number of ways, which can lead to inaccurate results in traditional impact assessment approaches. It also contributes to the field by doing a quality check on various matching algorithms and controlling for unobservable factors using a sensitivity analysis.

2. Literature Review

Agriculture is critical to global employment, revenue, and food security. Global actions aim to increase rural household welfare and encourage a smallholder-led agricultural revolution through improved agricultural practices, improved seed variety and fertilizer application, mechanization, and technology uptake (Chandra, Dargusch, McNamara, Caspe, & Dalabajan, 2017; D'Annolfo et al., 2021). This is critical for food security as well as welfare security. However, the adoption of improved agricultural technology interventions is sluggish due to obstacles such as adverse weather, liquidity, culture, risk aversion, and infrastructure limitations (Balana & Oyeyemi, 2022; Havemann, Negra, & Werneck, 2022). Farmers' adoption behavior is mostly impacted by subjective conditions and information offered (Zeweld, Van Huylenbroeck, Tesfay, & Speelman, 2017). Over the past few decades, global progress in food and nutritional security has been significant (Naylor et al., 2021; WHO, 2020). However, challenges remain, with malnutrition being a major concern. Undernutrition accounts for over 45% of fatalities among children under five, 1.9 billion obese adults, and 462 million underweight children (Dukhi, 2020;

Padhani, Das, Akhtar, Ismail, & Bhutta, 2022). This dismal data clearly demonstrates the intensity of the hunger issues faced by both children and adults. Given the detrimental implications of malnutrition, the United Nations has established many goals to tackle the problem through the promotion of NSA-related good practices across the world (Di Prima et al., 2022). The 2014 Second International Conference on Nutrition (ICN) assessed nutrition developments since 1992 and highlighted the need for nutrition-sensitive agricultural practices for food and welfare security(Meldrum, Padulosi, Lochetti, Robitaille, & Diulgheroff, 2018).

Nutrition-sensitive agriculture (NSA) is an approach that promotes food and welfare security by placing nutritionally rich and diversified food sources on the table to combat malnutrition and micronutrient deficiencies (Ruel, Quisumbing, & Balagamwala, 2018). The intervention aims to improve maternal and child nutrition while also empowering women. It is intended for mothers with children aged three to twelve months, and the intervention provides women access to agricultural training and inputs (such as equipment, seeds, and poultry) to promote small-scale agriculture and increase nutrient-rich food production. More crucially, the NSA approach pushes development agents to consider agricultural initiatives through the perspective of nutrition. NSA has become a globally adopted technique that allows for extensive adaptation to meet the particular bio-physical and socio-cultural characteristics of the target groups. The primary goal of NSA-based agricultural production is to make food abundant and accessible, diversified and sustainable, and healthy (Junuthula et al., 2023). The NSA strategy aims to dramatically improve poor people's nutrition, particularly that of mothers and small children (Nguyen et al., 2022). Agriculture impacts three key determinants of nutrition: food access, healthy environment, and adequate care practices. Food access refers to affordable, nutrient-dense foods available on farms and markets (Maestre, Poole, & Henson, 2017). Healthy settings ensure effective resource management, while care practices focus on women's empowerment, labor, and income (WHO, 2018). Welfare security is a complex issue that goes beyond food availability and variety. NSA intervention’s simplified impact pathways specify six outcomes for agriculture and nutritional interventions: on-farm availability, food diversity and safety, market food environment, income, women's empowerment, nutrition knowledge and norms, and natural resource management practices (Di Prima, Wright, Sharma, Syurina, & Broerse, 2020). These outcomes lead to improved diet and health, ultimately improving food and welfare security.

Agricultural interventions aiming at enhancing food and nutrition security usually focus on food production and consumption at the household level.

Developing household technical capacity for agricultural intensification and diversification is crucial to accomplishing this goal (De Roest, Ferrari, & Knickel, 2018). A favorable strategy should support long-term intensification and diversification to enhance NSA. Increasing production per unit of land or animal, as well as integrating complementing enterprises, are examples of how NSA might be accomplished (Pinillos, 2018). Increased access to crop and livestock inputs and services should be made possible with assistance. Households that can combine animal raising with crop production, particularly backyard vegetable and fruit cultivation, benefit nutritionally (De Roest et al., 2018). Producers of mixed crops and animals must be encouraged to undertake on-farm diversification. The increased and diversified output of nutrient-dense foods is critical for food and welfare security as well as market surpluses. The NSA intervention focuses on nutrient-dense food consumption for women of reproductive age (15–49 years) and children under two years of age (Bird, Pradhan, Bhavani, & Dangour, 2019; Gizachew, 2019). Other members of the family, however, might also engage in this pattern.

Empowering women is also critical for poverty reduction and welfare enhancement. There is a link between empowerment and better nutritional results (Baba, Kearns, McIntosh, Tannahill, & Lewsey, 2017). Women have been prioritized as beneficiaries of agricultural and nutrition programs. Autonomy, independence, ownership, self-awareness, agency, communal action, power redistribution, self-determination, participation, dignity, social inclusion, and choice are all facets of agricultural and nutritional empowerment. Women's empowerment comprises income, resource ownership, knowledge, and decision-making. NSA intervention affects these factors at varying rates and intensities, as measured by the Women Empowerment in Agriculture Index (FAO, 2018). Nutrition-based agricultural interventions have recently begun to include gender issues in their plans. This is due to women's importance in food production and consumption as well as their vulnerability to hunger and malnutrition. Children who receive inadequate care and feeding practices are more vulnerable to the detrimental impacts of malnutrition, which appear as stunting, wasting, and underweight, along with other deficiencies induced by malnutrition (De & Chattopadhyay, 2019). This improves people's well-being, prompting actions like NSA to attain the intended welfare benefits. To achieve this development goals, governments, donor institutions, and development organizations are increasingly supporting nutrition-sensitive agriculture.

3. Method

3.1 Theoretical Framework

The total consumption (food and non-food) spending is used as a measure of individual women's welfare to evaluate the influence of nutrition-sensitive agriculture on it. In order to investigate how NSA affects household welfare, Skoufias, Unar, and González-Cossío (2008) theoretical approach was applied. Let our utility function, which is composed of three factors: food consumption, non-food consumption, and leisure, be separable in its arguments. This assumption leads the study to develop the utility function as given below.

$$U = (fc, nfc, L) \qquad \textbf{(1)}$$

and the budget constraint will be

$$Pffc + Pnnfc + WL = \mho + W\Omega \qquad \textbf{(2)}$$

Where fc stands for food consumption, nfc stands for non-food consumption, and L stands for leisure from the utility function. Pf is the price of food consumption, Pnf is the price of non-food consumption, and W is the price of time in the budget constraint. In the same equation, Ʊ represents non-labor income, and Ω represents time endowment.

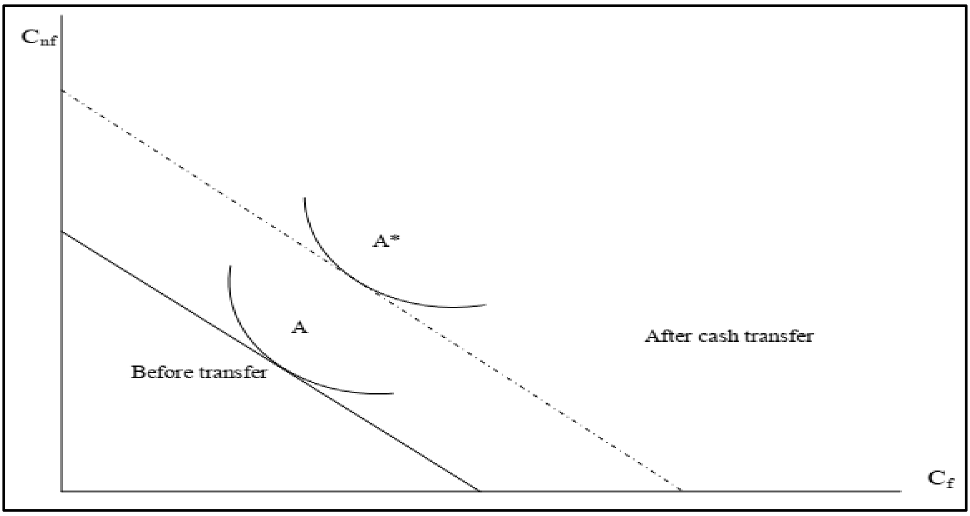
Women households seek to maximize utility $U = (fc, nfc, L)$ while adhering to the budget constraint $Pffc + Pnnfc + WL = \mho + W\Omega$. This leads to the following specification of the Lagrangian function (equation):

$$L = U = (fc, nfc, L) + \lambda(Pffc + Pnnfc + WL - \mho - W\Omega) \qquad \textbf{(3)}$$

Let's now employ graphical analysis to examine what transpires when a household implements a nutrition-sensitive agricultural intervention. The intervention of NSA N results in a parallel shift of the original budget line by $\frac{N}{pf}$ to the new dotted budget line to the right, as shown in Figure 1 below, and its impact on welfare is summed up by the shift of the optimal point from initial A to post-intervention A*. From Figure 1, it can be inferred that the intervention will probably lead to an increase in both food and non-food consumption. Mathematically, the first-order criteria describing the optimal choice of food and nonfood intake and leisure after the intervention are provided by the same ratio as those given above before the intervention at point A*.

At the equilibrium, at point A*, the maximization problem will yield:

$$\frac{Uf}{Unf} = \frac{Pf}{Pnf}, \frac{UL}{Uf} = \frac{W}{pf} \; and \; \frac{UL}{Unf} = \frac{W}{pnf} \quad \textbf{(4)}$$



The theoretical framework provides illustration of how NSA initiatives have raised household welfare. This shows that interventions will enhance the welfare of households. The technique described above shows that consumption expenditure (total consumption expenditure) may be employed as a stand-in for welfare in empirical studies. In other words, general consumer spending might stand in for the health of a home.

3.2 Method of Analysis

The analysis was done using descriptive statistics and propensity score matching method. Descriptive statics, such as percentages, mean, standard division, frequency, t-test, and cross-tabulations used to describe the socio-economic and plot-level factors (pre-intervention) influencing rural women household NSA participation in the program and then summarized by using inferential statics.

3.2.1 Propensity score matching (PSM) method

The NSA lacks a baseline survey and does not use randomization to determine participation. In other words, households that are eligible for selection are deliberately chosen based on their knowledge of the intervention and level of social security. Additionally, the baseline survey was not carried out before the NSA intervened in the study area. Thus, PSM uses observable characteristics of individuals in the sample to generate a control group that is comparable to the treated group conditional on identified exogenous factors, but different regarding the intervention status, here participation in NSA. There is a presumption of no unobserved heterogeneity differences between the control and treated group in PSM. To achieve the stated objectives, propensity score matching, which is often used to analyze the impact of a program, was utilized. Prior to the NSA intervention, it was presumed that socioeconomic and plot-level attributes were equivalent. The application of PSM entails five phases (Caliendo & Kopeinig, 2008). These involve evaluating the PSM, selecting a matching process, establishing if there is overlap (common support), estimating matching quality (effects), and doing a sensitivity analysis. The estimation of the propensity score is the first stage in the PSM technique. Conditional matching may only be done on P(X) rather than X when P(X) = Prob(D=1|X), which is the likelihood of participation in the program conditional on X (Rosenbaum and Rubin ,1983). These authors argue that if results without intervention are independent of participation given X, then they are also independent of participation given P(X), reducing a multidimensional matching issue to a single-dimensional problem. Choosing which model to use for the estimate and which variables to include in this model are both critical phases in calculating the propensity score.

For the binary treatment situation, the study assesses the likelihood of beneficiary vs. non-beneficiary using either logit or probit models that frequently produce similar findings. This is relevant to the choice of the kind of model to be employed. As a result, it is not a serious issue. However, the logit model is more popular for the estimation process (Caliendo & Kopeinig, 2008). The logit model was employed in this work to estimate the propensity score in order to fully exploit this advantage. The conditional independence assumption (CIA) dictates that the outcome variables be independent of treatment conditional on the propensity score. Thus, the matching method is based on identifying a set of variables X (covariates) that may effectively fulfill this condition. (Caliendo & Kopeinig, 2008). Basically, grasping economic theories, having a deeper grasp of earlier research, and being cognizant of institutional settings are all important guidelines for selecting the appropriate variables (Sianesi, 2004; J. A. Smith & Todd, 2005). The second stage in PSM is selecting among a variety of matching estimators after estimating the propensity score. It is possible to use a variety of PSM matching estimators (algorithms).

To get over the shortcomings of "nearest neighbor" matching and the danger of poor matches when the closest neighbor is far away, caliper and radius matching are utilized. In order to prevent poor matches and increase matching quality, caliper matching imposes a tolerance limit on the maximum propensity score distance. Caliper matching involves selecting a member of the comparison group as a matching partner for a treated individual who falls within the caliper (propensity range) and has the lowest propensity score. (Caliendo & Kopeinig, 2008). However, caliper matching does have the disadvantage of making it challenging to choose a suitable tolerance level in advance (J. A. Smith & Todd, 2005).

A common support condition is used to ensure that any combination of traits found in the treatment group may also be seen in the control group (White & Sabarwal, 2014). The average treatment impact on the treated and the population is only defined in the zone of common support; so, imposing common support is the third critical PSM step (Caliendo & Kopeinig, 2008; Kintamo, 2018). The area between the lowest and highest propensity scores of the treatment and comparison groups is known as the "common support region." This zone is established by removing observations with propensity scores that are lower than the minimum and higher than the maximum of the treatment and comparison groups, respectively (Abebe, Chalchisa, & Eneyew, 2021; Caliendo & Kopeinig, 2008).

Since our conditioning is based on propensity scores rather than all variables in both treated and comparison groups, the matching technique must be able to balance the distribution of different variables, which is the fourth crucial stage in PSM (Caliendo & Kopeinig, 2008; King & Nielsen, 2019). Although there are numerous ways for verifying, they are all basically implied to compare data before and after matching and determine whether there is still a difference after conditioning on propensity scores. If there are discrepancies, it shows that the matching failed and that remedial action is required. (Caliendo & Kopeinig, 2008; Shiba & Kawahara, 2021). There are several indicators that verify the quality of matching. The stratification test, the t-test, joint significance, pseudo-R2, and standardized bias are among these.

The last stage in PSM implementation would be to test the sensitivity of the estimated results (Caliendo & Kopeinig, 2008; Shipman, Swanquist, & Whited, 2017). The CIA, on which the matching method is based, states that the evaluator should consider all elements that influence the participation decision and outcome variables at the same time. This is the basis for this approach. However, since the data on the distribution of the untreated outcome for treated groups and vice versa are uninformative, this assumption is basically untestable. (Becker & Caliendo, 2007; Caliendo, Mahlstedt, & Mitnik, 2017). With matching estimators and the assumption that the observables have been chosen correctly, treatment effects are estimated. However, a hidden bias may develop if unobserved variables influence both the treatment assignment and the outcome variable at the same time, rendering the CIA incorrect. As a result, average treatment effect on the treated (ATT) estimates are biased (Corbacho, Philipp, & Ruiz-Vega, 2015; P. R. Rosenbaum & Rosenbaum, 2002). Testing the robustness of findings to deviations from the identification assumption is crucial since matching estimators are not robust against hidden biases. But using non-experimental data makes it hard to gauge the scope of selection bias. So, through sensitivity analysis, this issue may be solved (Caliendo & Kopeinig, 2008). It is advised that the Rosenbaum bounding technique be used to test the sensitivity of the estimated ATT to divergence from the CIA (P. R. Rosenbaum & Rosenbaum, 2002).

3.3 Data collection, Sample Size and Sampling Technique

3.3.1 Data collection

The cross-sectional data used in this study was gathered from primary sources. Using a structured questionnaire and a household level survey, primary data on the socioeconomic factors, agricultural characteristics, plot level features, resource ownership of the households, and other variables pertinent to the study were gathered. For ease of understanding between enumerators and respondents, a structured questionnaire produced in English was translated into Amharic. Then, in 2022, a household level survey was carried out on a sample of 260 households, of which 94 were farmers who engaged in NSA and the remaining 166 did not engaged in NSA, serving as a treatment group and a control group, respectively.

3.3.2 Sample Size Determination

Ethiopia has eleven regional administrative states, each subdivided into zones, districts, and kebeles[2]. The study was conducted in the Farta district of the

[2] The lowest administrative unit

South Gondar zone of Amhara Regional State. The total number of women targeted at the selected site was 745. So, the sample size was determined from the total number of women at a 95% confidence level with a 5% level of precision using Yamane's (1967) formula:

$$n=\frac{N}{1+N(e)^2}=\frac{745}{1+484(0.05)^2}=260$$

Where: n=sample size, N=total population (total number of dairy enterprises) e=level of precision.

3.3.3 Sampling Technique and Procedures

The NSA project implementing district was purposively selected from South Gondar Zone in consultation with South Gondar Agriculture Development Office. The district contains both participant and non-participant women with similar socioeconomic features, which are relevant to measure the extent of changes realized due to the NSA intervention. Multi-stage sampling procedures were employed to select the district, kebeles, and women. In the first stage, Farta district was purposefully selected because it is one of the beneficiary districts of the NSA intervention program. In the second stage, four kebeles were purposefully selected among the total of 31 kebeles due to their vulnerability to drought and as beneficiaries of the intervention. In the third stage, the total number of 745 women in the four selected kebeles was stratified into two strata: NSA intervention participant and non-participant women among the sample frame, which are listed down as participant and non-participant in the March 2021–2022 agricultural season in each selected kebele’s administrative office. In the fourth stage, representative samples were selected from each kebele using the systematic random sampling technique by the constant k number of intervals, where k = N/n = 3, based on the probability proportional to sample size. Finally, 260 (166 non-participant and 94 participant) sample households were selected. Women of reproductive age, including mothers and caretakers with children under the age of two, were included in the formal, structured questionnaire interviews. Finally, two plots of information were taken from each female-headed household. The following table shows the sampling distribution of households by Kebele.

Table 1: Proportional Distribution of Samples by Kebeles

Kebeles	Total Number of women in kebeles			Sample size from each kebele $n_i3 = {N_i}/{N} * n$		
	Participant	Non-participant	Total	Participant	Non-participant	Total
Worken	65	101	166	20	38	38
Awuzet	80	108	188	25	40	65
Sahirna	73	118	191	23	44	67
Kolay Dengorse	81	119	200	26	44	70
Total	299	446	745	94	166	260

3.4 Description of variables included in PSM

Table 2: Definition and Measurement unit of variables

Variables	Description	measurement unit
Household level characteristics		
hhsize	Size of household's members	number
headsex	Gender of household head	dummy
headage	Age of household head	years
headed	Education level of household head (1=male 0=otherwise)	dummy
maritalstatus	Marital status of household head (1=married 0=otherwise)	dummy
dependratio	The ratio of dependent household members to non-dependent	number
livestock	Total number of livestock	TLU
extvisit	Numbers of extension visit per year	number
shock	Households affected by health shock (1=yes 0=no)	dummy
radio	Radio ownership (1=yes 0=no)	dummy
Plot level characteristics		
plotdist	Plot distance from homestead	minutes
irrigation	Plots irrigate (1=irrigated 0=Otherwise)	dummy
poor	Soil type (1=poor 0=0therwises)	dummy
fair	Soil type (1=fair 0=0therwises)	dummy
good	Soil type (1=good 0=0therwises)	dummy
steep	Terran nature (1=steep 0=0therwises)	dummy
moderate	Terran nature (1=moderate 0=0therwises)	dummy
flat	Terran nature (1=flat 0=0therwises)	dummy
Intervention		
NSA	Nutrition sensitive agriculture4	dummy
Outcome		
totalexp	Total consumption expenditure	Birr

[3] Where n_i is sample size in ith kebele, N_i is total population of the household in ith kebele and N is total population of households in the selected kebeles.

[4] NSA intervention is a nutrition-sensitive investment which intends to ensure better nutrition. The participants received training, advice, seed and poultry that can help them to improve their production and consumption.

4. Results and Discussion

4.1 Descriptive statistics

The results and discussion part provide a full explanation of the study's findings, which are described below in two sub-sections. Women's socioeconomic and plot-level characteristics related to rural women's welfare are discussed in the first part. The next parts deal with the impact of NSA intervention on welfare outcomes.

Table 3 revealed that participant women's average family size was less than that of non-participant women, and the entire sample average family size is close to 5, which is similar to the national average of 5 (UN, 2017). The t-test indicated that there were statistically significant differences. The mean age of participant women was 52 years, whereas non-participant women had an average age of 54.9 years, and no statistically significant difference was found for this covariate. The mean dependence ratio of participant women was 1.28, while non-participant women had a dependency ratio of 1.87, indicating that on average, one economically independent household member supports 1.28 dependents for participant women and 1.87 dependents for non-participant women. Women who participated in the program received visits from extension officers 4.15 times a year on average, whereas women who did not participate received 1.47 visits from extension development agents. The t-test result revealed a statistically significant difference in extension visits between the two groups. In terms of livestock ownership, participant women outnumbered non-participant women by a statistically significant margin. Finally, the average yearly total spending of non-participating women was birr 8552.9, whereas participant women spent birr 10,229.61. This suggests that the average spending of the participant women was more than that of their counterpart, with a statistically significant difference.

Table 3: Descriptive statistics of continuous variables

Variables	Non-Participant			Participant			P-value
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
hhsize	166	5.33	2.115996	94	4.45	1.89	0.000***
headage	166	54.92	15.44906	94	52.05	16.07	0.156
dependratio	166	1.87	1.110816	94	1.28	0.98	0.000***
extvisit	166	1.47	2.567163	94	4.15	3.75	0.000***
livestock	166	1.97	1.74	94	2.69	2.41	0.005***
totalexp	166	8613.231	3902.61	94	10,375.14	3680.99	0.000***

*** 1% level of significance
Own computation (2022)

Table 4 below showed that 48% of participant women and 34% of non-participant women were literate. The chi2 test revealed that there is a statistically significant difference in education status. The percentage of married women was 80% among participants and 72% among non-participants, with no discernible difference between the two. In addition, 57% of non-participant women and 61% of participant women reported having suffered health shocks at least once during the study period. Twenty-two percent of participant women and 20% of non-participant women had radios that enables them to get access for various sources of information.

Table 4: Descriptive statistics of household level dummy variables

Variables	No-Participant			Participant			P-value
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
headedu	166	0.34	0.48	94	0.48	0.50	0.099**
maritalstatus	166	0.72	0.45	94	0.80	0.40	0.180
shock	166	0.57	0.50	94	0.61	0.49	0.838
radio	166	0.22	0.41	94	0.20	0.40	0.236

** 5% level of significance
Own computation (2022)

Table 5 shows that the average distance of farm plots from home for participant and non-participant women was 19.5 and 21.7 minutes, respectively. This suggests that non-participant women plot sites further away than participant women.

Table 5: Descriptive statistics of plot level continuous variables

Variables	Participant			Non-Participant			P-value
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
plotdist	332	21.71	22.1	188	19.24	19.54	0.212

** 5% level of significance
Own computation (2022)

Table 6 shows that only 7% and 9% of plots were irrigated by participant and non-participant women, respectively, implying that the most of plots cultivated by both participant and non-participant women relied on a rainfed farming system. Furthermore, 45% of plots had fertile soil, 40% possess good soil fertility, and 15 percent had poor soil quality. In terms of plot terrain, 67% of plots had a moderate slope, while 17% had a flat slope. The slopes of the remaining 16% of plots were steeper.

Table 6: Descriptive statistics of plot level dummy variables

Variables	Participant			Non-Participant			P-value
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
irrigation	332	0.07	0.26	188	0.09	0.29	0.201
poor	332	0.15	0.35	188	0.07	0.26	0.014**
fair	332	0.40	0.49	188	0.48	0.50	0.075*
good	332	0.45	0.50	188	0.45	0.50	0.889
steep	332	0.16	0.37	188	0.11	0.32	0.157
moderate	332	0.67	0.47	188	0.77	0.42	0.020**
flat	332	0.17	0.38	188	0.12	0.33	0.096*

*** 1%, ** 5%, * 10% level of significance
Own computation (2022)

4.2 Impact of NSA on Women Welfare (PSM Result)

The model found that there exists a close socio-economic and plot level character similarity between the NSA participant and the non-NSA participant (control) women. The outcome variables that are being tested for the changeover NSA intervention were annual consumption expenditure of women. It is customary to run the multicollinearity and heteroskedasticity tests in most of economics related research studies. However, these tests were not conducted in the present study. The reasons for this include, the fact that heteroskedasticity error terms have little influence on the estimated intervention impact in propensity score matching (Williams, 2012). And also no multicollinearity test conducted as there is one explanatory term per estimation (Gujarati & McGraw-Hill, 2004).

The probability of participation is predicted on the basis of the selected parameters that represent meaningful observable differences between participants and non-participants women. When single observables are examined, it is found that household size, head age, dependency ratio, plot distance have a negative significant influence on decision to participate in NSA while head education, marital status, irrigation access, extension visit, livestock holding, level of soil fertility, and terrain nature all had positive significant influence on households' participation decisions in the NSA program (see Table 7 in the appendices).

To match the treated and its comparison group, the propensity score of women was computed based on their individual characteristics. The propensity score results indicated that the required balancing property of the distribution of propensity scores is satisfied. Most of participant women and non-participant women had a common support region, only two participant women were outside the common support region and therefore discarded from the matched sample (see table 8 in the appendices). The main aim of checking the common support region was to identify the households that were in the same range of observable socio-demographic, economic, and plot-level characteristics in the two groups (see table 9 in the appendices).

The radius caliper (RC) matching with band width 0.25 was chosen as the most desirable matching estimator since it fulfils the three desirable criteria, i.e., the equal means test, which is referred to as the balancing test (Dehejia & Wahba, 2002). Thus, the average treatment effect of the program on the treated was estimated for the matched households on the basis of this robust matching estimator. It was the after-matching phenomenon that indicated that the tests of whether there was a significant difference between the characteristics of the participant and non-participant women after balancing them based on their propensity score through the radius caliper 0.25 of the matching estimator. However, in principle, there must not be any significant difference between those covariates after matching processes. Accordingly, the T-values also revealed that, from a total of 14 covariates, 13 became insignificant after matching, while 11 of them were significant before matching (see table 10 in the appendices).

This matching process can equalize features between the treated and matched comparison groups. As a consequence, the findings may be utilized to evaluate the impact of NSA participation across groups of households with comparable observable characteristics. All of the above tests indicate that the matching method used is suitable for the data at hand. As a result, the study proceeds to estimate the average treatment impact on the treated (ATT) for the sample households.

4.3 Average Treatment Effect on the Treated

The impact estimate demonstrated that participation in NSA had significant effects on welfare in the study area since the average treatment effect on the treated after matching is positive and the t-calculated is more than the 5% critical value of 1.96. The higher impact of the NSA on welfare found in stud study might be attributed to the fact that households in the study area were completely targeted. Furthermore, the average treatment effects on the treated (ATT) of welfare are 1623.4 birrs per year (10267.04 birrs for treated group and 8643.6 birrs for the controlled group), and the positive difference, as well as the t-calculated 3.10, indicated that nutrition-sensitive agriculture programs had a statistically significant positive impact on women welfare (see Table 11 in the appendices). Similar studies by Gizachew (2019) and Mucheye (2021) confirms that the NSA intervention have had positive, although at varying degrees, influence on women empowerment, productive resource ownership, dietary varieties and welfare. The study confirmed that participation in the NSA improves welfare via reducing the likelihood that a household has become very low caloric intake as well as enhancing women's non-food consumption spending.

4.4 Sensitivity Analysis Results

To estimate the extent to which such selection on unobservable may bias our inferences on the effects of the program, sensitivity analysis was conducted. One strategy to address this problem is the Rosenbaum and Rubin (1983) approach, which allows the analyst to decide how strongly an unobserved variable may affect selection in the treatment. If there are unobserved variables that simultaneously affect selection into treatment and the outcome variable, a hidden bias might arise to which matching estimators are not robust (Rosenbaum & Rubin, 1983). The result of this study indicates that the inference of the effect of the program is not varying though the participants and non-participants women have been allowed to differ in their odds of being treated up to (maximum value of gamma 2 with 0.25 increments) in terms of unobserved covariates. Therefore, it can be concluded that our impact estimates of welfare were insensitive to unobserved selection bias and were the result of pure effect of the program which is participating in the program (see Table 12 in the appendices).

5. Conclusion and Policy Recommendation

5.1 Conclusion

This study examined how the NSA intervention impacted welfare outcomes of rural women. The study area's socio-demographic, economic, and plot-level factors that determine women's ' decision to participate in NSA were investigated. The study relied heavily on primary data collected from 260 randomly selected sample households from four kebeles, with 166 non-participants and 94 participant women. As a result, data on women welfare were collected from both participant (treatment) and non-participant (control) households using plot-level cross-sectional data and analyzed using descriptive statistics as well as econometric approaches.

Impact evaluation based on treatment-control comparisons can be inaccurate due to selection bias, but propensity score matching can be used to acquire accurate estimates due to the difference between matched participants and non-participants being attributable to the therapy. Significant and robust differences are found for nutrition-sensitive agriculture between matched participants and non-participants based on the quality check of standardised differences and the control of the unobservable by Rosenbaum's bounds. So, the nutrition sensitive agriculture program had brought a significant positive effect on women welfare. The significant impact of NSA on women welfare might be because participant households in the study area had been full targeted.

5.2 Recommendation

The empirical findings led to the following recommendations:

The intervention had a positive impact on welfare this will mainly require a special attention by policy makers and concerned bodies and it should be scaled up to the other areas.

Since the implementation of the program is limited to districts where development agents and NGOs operates, for wider implementation of the intervention, the NSA approach should be incorporated in the regular extension programs with the required resources.

The NSA program initially assumed full family targeting for the poor of beneficiaries in order to fill the gap of welfare. However, the finding indicates that participant households were not full family targeted and there by decrease the welfare they have gotten from the program. Therefore, a special attention should be given by a concerned body.

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Appendices

Table 7: logit regression to predict propensity scores of participations conditional on selected variables

Variables	cofe	P-val
hhsize	-0.455***	[0.000]
headage	-0.014*	[0.050]
headedu	0.416*	[0.091]
maritalstatus	1.050***	[0.001]
dependratio	-0.532***	[0.000]
shock	0.438*	[0.096]
irrigation	1.017**	[0.015]
extvisit	0.309***	[0.000]
livestock	0.215***	[0.000]
plotdist	-0.012**	[0.032]
fair	0.766	[0.334]
good	0.910**	[0.029]
moderate	0.621*	[0.070]
flat	0.936**	[0.048]
Constant	-0.290	[0.689]
Observations	520	

*** 1%, ** 5%, * 10% level of significance

Own computation (2022)

Table 8: distributions of estimated propensity score for participant and non-participant

	Variable	Obs	Mean	Std. Dev.	Min	Max
Non-participant	_pscore	188	0.231143	0.218726	0.004136	0.977853
Participant	_pscore	332	0.5833097	0.250255	0.049054	0.9902

Own computation (2022)

Table 9: The Common Support Region

psmatch2: Treatment assignment	psmatch2: Common support		Total
	Off support	On support	
Untreated	0	332	332
Treated	2	186	188
Total	2	518	520

own computation (2022)

Table 10: Tests of covariate matching quality

Variable	Unmatched Matched	Mean Treated	Mean Control	t-test t	t-test p>t
hhsize	U	4.4468	5.3313	-4.77	0.000***
	M	4.4409	4.7985	-1.89	0.060*
headage	U	52.053	54.928	-2.01	0.045**
	M	51.978	51.888	0.06	0.955
headedu	U	.44681	.34337	2.34	0.020**
	M	.44086	.51481	-1.43	0.154
maritalstatus	U	.79787	.72289	1.90	0.058*
	M	.7957	.80056	-0.12	0.907
dependratio	U	1.2785	1.8673	-6.07	0.000***
	M	1.2842	1.4092	-1.35	0.178
shock	U	0.5531	0.56627	-0.29	0.773
	M	0.55435	0.60479	-0.98	0.328
irrigation	U	.10638	.06024	1.90	0.058 *
	M	.09677	.09712	-0.01	0.991
extvisit	U	4.1489	1.4759	9.62	0.000 ***
	M	4.0753	3.4521	1.59	0.114
livestock	U	2.6983	1.972	3.98	0.000***
	M	2.6903	2.5361	0.65	0.518
plotdist	U	19.245	21.711	-1.25	0.212
	M	19.355	19.924	-0.27	0.790
fair	U	.04255	.01205	2.23	0.026**
	M	.04301	.03686	0.30	0.763
good	U	.90426	.80723	2.94	0.003 ***
	M	.90323	.90227	0.03	0.975
moderate	U	.77128	.6506	2.89	0.004***
	M	.76882	.78213	-0.31	0.759
flat	U	.12766	.08434	1.58	0.114
	M	.12903	.12012	0.26	0.795

* if variance ratio outside [0.75; 1.33] for U for M

*** 1%, ** 5%, * 10%

own computation (2022)

Table 11: Average Treatment effect on the treated

Variable Sample	Treated	Controls	Difference	S.E.	T-stat
totalexp unmatched	10375.1	8613.2	1761.9	360.7	4.88***
ATT	10342.5	8910.3	1432.2	461.9	3.10***

*** 1%,

own computation (2022)

Table 12: Sensitivity analysis with ROSENBAUM'S bounds

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	8748.35	8748.35	8664.09	9030.19
1.25	0	0	8432.93	8466.01	8958.82	9381.23
1.5	0	0	8187.24	8348.34	8928.82	9662.83
1.75	0	0	8290.12	8580.18	8940.35	9925.11
2	0	0	8337.63	8789.86	8774.81	9157.4

sig+ - upper bound significance level

sig- - lower bound significance level

t-hat+ - upper bound Hodges-Lehmann point estimate

t-hat- - lower bound Hodges-Lehmann point estimate

CI+ - upper bound confidence interval (a= .95)

CI- - lower bound confidence interval (a= .95)

Own computation (2022)