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The impact of safety net programs on household asset building in Ethiopia: Propensity scope matching model results

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The study analyzed the impact of the Productive Safety Net Program (PSNP) on Household Asset Building (HAB) in drought-prone areas of Southern Ethiopia. Cross-sectional survey data were collected from 180 randomly sampled households, including both PSNP beneficiaries and non-beneficiaries. The analysis included both inferential and descriptive methods, utilizing a Propensity Score Matching (PSM) technique to estimate the inferential results. The study's findings indicate that the PSNP has positively influenced the asset holdings and consumption patterns of beneficiary households compared to non-beneficiary households. However, the impact varied based on the type of intervention the beneficiaries accessed. Those who participated in the HAB program were more likely to improve their asset status, reduce asset depletion, and ensure consistent consumption throughout the year. Challenges identified in the study include delays in resource transfer and limited coverage of households, which hindered the program's effectiveness. The study concludes that timely resource transfers and expanded household coverage are essential for scaling up the program's impacts in the future.

Key words: Household asset-building, safety-net program, Propensity Score Matching (PSM), droughts.

INTRODUCTION

Persistent shocks leading to the depletion of household assets pose ongoing challenges for the livelihoods of smallholder farmers and pastoralists in Ethiopia. This not only burdens the government and humanitarian actors but also underscores the need for effective asset recovery interventions, especially given the growing population and its demands (Gilligan et al., 2008; Andersson et al., 2009; Tasew and Tariku, 2022; Guush et al., 2011).

Despite government efforts and aid inflow from global actors focusing on household asset-building and environmental rehabilitation in drought-affected areas, the problem persists, compounded by the unfolding and dynamic impacts of climate change (Birhanu, 2009; Okocha and Akpe, 2022; McLaughlin et al., 2023). In the face of resource scarcity and the increasing impact of droughts and climate change, households in Ethiopia

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deplete 72 to 75% of their assets and struggle to recover (UN, 2010; Gashaw and Seid, 2019; Zerhun, 2020; Tareke, 2022).

Recurrent drought shocks create a vicious cycle of poverty for households in drought-prone areas, making it challenging to break free from this cycle (Haan et al., 2006; Abdulhakim et al., 2022). Over the last three decades, at least 10 to 12 million people in Ethiopia have received food aid or participated in food/cash-for-work programs within the framework of PSNP Ethiopia (Gashaw and Seid, 2019; Zerhun, 2020).

The context is further exacerbated in areas such as Beneshangul Guuz, Gambella, SNNPR, and Somali regions due to the influx of refugees, internal displacements resulting from conflicts and wars in Ethiopia (Abdi et al., 2023; Fantu and Minten, 2023). Initiated in 2005, the PSNP, with an annual budget of nearly 500 million USD, reaches more than 7 to 12 million people in Ethiopia (Tasew and Tariku, 2022). Complemented by Other Household Asset Building Programs (OFSP), the PSNP aims to protect existing assets and ensure a minimum level of asset recovery, while the OFSP focuses on encouraging households to increase income from agricultural activities and build more assets (Fantu and Minten, 2023).

Despite Southern Ethiopia being a beneficiary of the PSNP since February 2005, the initial impact studies focused on Northern and Eastern Ethiopia. Furthermore, even in regions with relatively better weather, water, and land resources, it remains unclear why PSNP beneficiary households are not building assets and graduating from PSNP aid after three decades. This study aims to understand the reasons behind the lack of graduation among PSNP beneficiaries, identifying empirical, and policy practice gaps related to PSNP interventions in Southern Ethiopia.

LITERATURE REVIEW AND ANALYSIS FRAMEWORK

The PSNP conceptualizes asset building at institutional, community, and household levels (Kaleab et al., 2014; Guush et al., 2017a; Girmay, 2020; Fantu and Minten, 2021). Institutionally, diverse development actors, governments, and donors pool resources to implement the program as a consortium of actors (Fantu and Minten, 2023). At the community level, beneficiaries are incentivized through cash and food aid to participate in environmental rehabilitation on both communal and private lands (Del-Ninno et al., 2004; Emerta et al., 2020; Fantu and Minten, 2023; Addisalem et al., 2023). At the household level, the program provides cash, farm inputs, livestock replenishment, etc., aiming to reduce asset depletion and support rapid recovery after shocks (Zerhun, 2020; Tareke, 2022).

Smallholder farmers and pastoralists view asset stability in the face of dynamic shock impacts as critical for their livelihoods, considering assets and livestock as a form of insurance (Khasnobis et al., 2007; Dagne, 2009; Haan et al., 2006; Girmay, 2020; Fantu and Minten, 2023). HAB interventions, in the context of recurrent shocks, require support in the domains of production, exchange, and transfer/aid due to contextual and institutional factors (Girmay, 2020). PSNP's asset-building support expands household entitlements to a diverse set of assets (both communal and private), helping address supply constraints during shocks (Tirame, 2008; Gashaw and Seid, 2019; Zerhun, 2020; Tareke, 2022). Studying asset-building interventions and their impact at the household level is argued to generate useful policy and theoretical information regarding entitlements to critical assets during shocks (Bonfiglioli, 2009; Hoddinott, 1999a, b; Birhanu, 2009; Raisin, 2003).

The PSNP aims to reduce household and communal poverty (increasing livestock and crop production, reducing environmental degradation) and serves as a redistribution mechanism and shock mitigator, ensuring recovery through asset building (Azadi et al., 2017; Emerta et al., 2020; Girmay, 2020; Addisalem et al., 2023). It also creates a fallback capacity for households in the face of shock dynamics, preventing the vicious cycle of asset depletion in recurrent drought settings (Besley et al., 2003; Gilligan et al., 2008; FAO, 2009; Shimelis, 2009; Girmay, 2020). The PSNP provides smallholder farmers with greater flexibility over consumption decisions and stimulates rural market development (Mendola, 2007; Fantu and Minten, 2023; Addisalem et al., 2023).

Initiated in 2005, the PSNP aimed to shift Ethiopia's system dominated by emergency humanitarian aid to a productive and protective safety net system through a multi-year resourcing framework (FAO, 2009; Tirame, 2008; Guush et al., 2017). The PSNP, through collective engagement and cooperation of development actors, addresses immediate human needs while supporting the rural transformation process, preventing long-term consequences of consumption shortages and asset depletion, encouraging production and investment, and promoting market development by increasing household purchasing power (Guo et al., 2004; Abdulhakim et al., 2022; Tareke, 2022). It targets chronically poor smallholder households (Sharp et al., 2006; Devereux and Guenther, 2007; Gashaw and Seid Nuru, 2019), saving assets and lives of millions in drought-prone areas. However, the expected outcomes were not fully achieved, and millions of households continue to rely on external aid (Tirame, 2008), with environmental degradation remaining unabated (Addisalem et al., 2023). The PSNP aims to provide "predictable transfers to meet predictable needs," addressing the consumption gap, protecting assets against distress sales, and building resilience against shocks (Girmay, 2020; Fantu and Minten, 2021). The "Public Works Program" offers temporary employment to the majority of PSNP participants (85%) in rural infrastructure projects such as road construction (Addisalem et al., 2023). "Direct Support" provides unconditional transfers to beneficiaries (15%) in households with no able-bodied members (Gilligan et al., 2008; Guush et al., 2011; Tasew and Tariku, 2022). Complementary programs like "livelihood packages" generate secondary streams of income until the household is assessed as recovered from shock impacts and ready to graduate from dependency on food/cash transfers (Gelebo, 2010). While emergency relief may still be required in severe shock years, the success of the PSNP could remove millions from the annual emergency appeal list, gradually shifting towards a flexible multi-year safety net aligned with the development needs of households and communities in drought and shock-affected areas (Bahru et al., 2021; Hailu and Amare, 2022).

The effective implementation of the PSNP is impacted by economic, institutional, technological, socio-psychological, demographic, and vulnerability factors. These factors will continue to influence household consumption patterns and asset depletion dynamics in the context of droughts, determining the outcomes of PSNP asset-building support.

MATERIALS AND METHODS

PSM estimation

Research approach, design and methods

The study employed quantitative approach, and an experimental research design. The quantitative data were collected from primary sources, from beneficiary household survey and were analyzed using both descriptive statistics and econometric model. The descriptive statistics analysis included mean, variance, standard deviations, percentages and chi-square test results. These data sets were used to assess the socio-economic situation of the respondents in regard to benefits from the PSNP, including targeting.

The inferential statistics analyzed in the study was estimated by PSM model. The motivation to use the PSM methods emanated from the dimensionality of the variables observed in this study. With a small number of characteristics (for example, two binary variables), matching is straight forward (one would group units in four cells). However, when there are many variables, it is difficult to determine along which dimensions to match units or which weighting scheme to adopt. Propensity score-matching methods, as demonstrated in this study, are especially useful under such circumstances because they provide a natural weighting scheme that yields unbiased estimates of the treatment impact (Shimelis, 2009; Raisin, 2003; Wooldridge, 2016). The PSM gives an unbiased evidence and policy information, in the context of impact evaluation and will better inform policy decisions (Wooldridge, 2016).

Using PSM constructs a statistical comparison group by matching non-beneficiaries to beneficiaries using observable characteristics from before the program that are correlated with the probability of being in the program and with the outcome variables of interest. The method better estimates impact and predict the probability of each household receiving the PSNP on a sample of PSNP beneficiaries and non-beneficiaries. Each beneficiary household is then matched to one or more non-beneficiary households based on having a similar estimated probability of being in the program, or “propensity score.” Using this sample of matched beneficiaries and non-beneficiaries the impact estimate is then constructed as the average difference in beneficiary outcomes and a weighted average non-beneficiary outcome, using the propensity scores to construct the weights (Gilligan et al., 2011; Wooldridge, 2016).

This PSM also extract from the sample of non-participating households a set of matching households that look like the participating households in all relevant pre-intervention characteristics. In other words, PSM matches each participant household with a non-participant household that has (almost) the same likelihood of participating into the *PSNP* (Wooldridge, 2016). In this study, the PSM is estimated as follows.

The first step in PSM method is to estimate the propensity scores. Matching can be performed conditioning on P(X) alone rather than on X, where P(X) = Prob (D=1|X) is the probability of participating in the program conditional on X. If outcomes without the intervention are independent of participation given X, then they are also independent of participation given P(X) (Shimelis, 2009). In other words, PSM matches each participant household with a non-participant household that has (almost) the same likelihood of participating into the program. This reduces a multidimensional matching problem to a single dimensional problem. In the case of the study in hand, control groups (non-users) are those who pass the criteria to be chosen or eligible for the program.

A logit model was used to estimate propensity scores using a composite of pre-intervention characteristics of the sampled PSNP beneficiary households (Wooldridge, 2016) and matching was then performed using propensity scores of each observation. The logit model estimates the dependent variable, the participation in PSNP. The dependent variable takes the value 1 if the household participated in the program and 0 otherwise. The mathematical formulation of logit model was as follows (Equation 1):

$$\mathrm{pi} = \frac{e^{zi}}{1+e^{zi}} \tag{1}$$

where Pi is the probability of participation (Equation 2),

$$Zi = a_0 + \sum_{i=1}^{n} \mathrm{aiXi} + \mathrm{Ui} \tag{2}$$

where i = 1, 2, 3,…..n; a0 = intercept; ai = regression coefficients to be estimated; Ui = a disturbance term, and Xi = pre-intervention characteristics.

The probability that a household belongs to non-participant is (Equation 3):

$$1 - pi = \frac{1}{1+e^{zi}} \tag{3}$$

The logit model via the PSM generates better estimation results including in the case of predictor/explanatory variables, that is, the participation in the PSNP and the outcomes (Bryceson et al., 2002; Wooldridge, 2016). Though several factors affect the selection of predictor variables, this study identified explanatory variables of the logit model and data from the program document and field observation. The study included as many explanatory variables as possible to minimize the problem of unobservable characteristics in the analysis of the PSNP impact on *HAB*.

Matching estimators, region of common support condition, and balancing tests

In this sub topic, the matching estimators, the region of common support condition and balancing tests were presented. Regarding matching estimators, all matching estimators analyze the outcome of a treated individual with outcomes of the comparison. In this respect, the PSM estimators differ: in the way the neighborhood for each treated individual is defined and the common support problem is handled; and in respect to the weights assigned to these neighbors (Caliendo, 2005; Wooldridge, 2016). A major task of program evaluator after estimating the propensity scores is seeking the appropriate matching estimator. Out of the matching estimations available in existing theories, Nearest Neighbor (NN), the Caliper Matching, and the Kernel Matching justifications were as follows.

Nearest neighbour matching

The NN matching is the most straightforward matching estimator (Caliendo and Kopeing, 2008). It considers a matching partner for a treated individual that is closest in terms of propensity score. In this matching, the participants and non-participants are randomly ordered in line with the closest propensity score (Guo et al., 2004; Wooldridge, 2016). The result in increased quality of matches and decreased precision of estimates depend on NN matching without replacement, a comparison individual can be used only once. In cases where the treatment and comparison units are very different, finding a satisfactory match by matching without replacement can be very problematic (Shimelis, 2009; Wooldridge, 2016). Therefore, by matching without replacement, when there are few comparison units similar to the treated units, the match is conducted among the treated units to comparison units that are quite different in terms of the estimated propensity score.

Caliper matching

The NN matching faces the risk of bad matches if the closest neighbor is far away (Caliendo and Kopeinig, 2008). In this case, by imposing a tolerance level on the maximum propensity score distance (or calipers), the caliper matching is used as one form of imposing a common support condition. Applying caliper matching considers a matching partner for a treated individual that lies within the caliper (‘propensity range’) and is closest in terms of propensity score. However, it is difficult to know *a-priori* what choice for the tolerance level is reasonable (Suresh, 2009; Chen and Krissey, 2008). A benefit of caliper matching is that it uses only as many comparison units as are available within the calipers, allowing for the use of extra (fewer) units when good matches are (not) available (Dehejia and Wahba, 2002) and the smaller the size of the neighbourhood the better is the quality of the matches (Besley et al., 2003).

Kernel matching

The Kernel matching considers all treated units matched with a weighted average of all controls with weights which are inversely proportional to the distance between the propensity scores of treated and controls (Besley et al., 2003; Wooldridge, 2016). Kernel weights the contribution of each comparison group member so that more importance is attached to those comparators providing a better match. In this matching, the use of the normal distribution (with a mean of zero) as a kernel weight is attached to a particular comparator, and is considered proportional to the frequency of the distribution for the difference in scores observed (Bryceson et al., 2002). The drawback of this method is that bad matches could be used as the estimator includes comparator observations for all treatment observation (Caliendo and Kopeinig, 2008; Wooldridge, 2016). Thus, a proper imposition of the common support condition is of major importance for kernel matching and a practical objection to its use is that it will not be obvious how to set the tolerance. According to Mendola (2007), a kernel with 0.25 band width is mostly used.

Regarding the region of common support condition, according to Bryceson et al. (2002), imposing common support condition ensures that any combination of characteristics observed in the treatment group can also be observed among the control group. The common support is the region where the balancing score has positive density for both treatment/beneficiary and control/non-beneficiary units. No matches can be formed to estimate the TT parameter (or the bias) when there is no overlap between the treatment and control groups. We define the region of common support by dropping observations below the maximum of the minimums and above the minimum of the maximums of the balancing score. The overlap condition for persons with the same x value in X are allowed to have a positive probability of being in treated and control group. The inferences were made based on sufficient data. Unlike ordinary regression, we don’t extrapolate outside the range of the observed data points (Wooldridge, 2016).

Regarding the balancing test, the two-sample t-test can be used to check if there are significant differences in covariate means for both groups. Before matching, differences between the groups are expected; but after matching, the covariates should be balanced in both groups and hence no significant differences should be found. The t-test might be preferred if the evaluator is concerned with the statistical significance of the results (Caliendo and Kopeinig, 2008; Wooldridge, 2016). Finally, using predicted probabilities of participation in the program (that is, propensity score) match pairs will be constructed using alternative methods of matching estimators. Then the impact estimation is the difference between simple mean of outcome variable of interest for beneficiary and non-beneficiary households. In this case, the mean stands for household asset protection in birr and changes in food consumption six years. The mean impact of *PSNP* on asset prevention and food consumption assurance of household is given by Equation 4:

$$\Delta C = \frac{1}{N_T} \sum_{i\varepsilon\{D=1\}} \left[y_1, i - \sum_j w(i,j)\, y_0, j \right] \quad (4)$$

where ΔC is average mean of the treatment of treated, y is out come variables 0< $w(i,j) \leq$ 1 and {D =1} is the set of treated individuals, j is an element of the set of matched comparison units, N_T is the number in the treated group, i is treated individual. Thus, different matching estimators are generated by varying the choice of $w(i,j)$.

The independent variables were identified as a combination of vulnerability, economic, demographic, institutional, technology, and socio-psychological factors.

The dependent variable is the participation of households in the PSNP. The outcome variables identified were improvements in household food consumption and prevention of asset depletion in the context of droughts and shocks in the study area. The variables are presented in Table 1.

RESULTS AND DISCUSSION

Descriptive data analysis

A descriptive statistics and analysis were presented here.

Table 1. Variable definition and measurement.

Definition of factors	Types and definition	Measurement	Hypothesis
Dependent variable (PSNP positively impact on participant, and no for none participant of PSNP)			
Participation in PSNP	Dummy, participation in the PSNP	1 if yes, 0 otherwise	+/-
Vulnerability factors (HH capacity/buffer shock impacts and recover)			
Sex of HHH	Dummy, sex of household head	1 if male, 0 otherwise	+/-
Literacy of HHH	Numerical, literacy status of HHH	1 if read & write, 0 otherwise	+/-
Family size of participant HH	Numerical, household size	Number, of family members	-
Land size of participant HH	Numerical, landholding size	HH landholding in hectares	+
Participant HH dependency ratio	Numerical, in-active vs. active labor	Ratio	-
Participant HH access to credit	Dummy, participation in credit	1 if yes, 0 otherwise	+
Participant HH access to farm extension	Dummy, extent of participation	1 if yes, 0 otherwise	+
Participant HH use of improved seed	Dummy, use of improved seed	1 if yes, 0 otherwise	+
Participant HH use of inorganic fertilizer	Dummy, use of fertilizer	1 if yes, 0 otherwise	+/-
Asset protection/building outcome variables			
Participant HH livestock ownership (TLU)	Numerical, livestock owned	in TLU	+
Participant HH total farm income	Numerical, total farm income	in birr	+
Participant HH total off/non-farm income	Numerical, off/non- farm income	in birr	+
Participant HH expense on housing	Numerical, expenditure on housing	in birr	+
Participant HH expense on equipment	Numerical, expense on farm tools	in birr	+

Source: Researcher's hypotheses summary, 2023.

Table 2. Descriptive analysis of sample household pre-intervention characteristics.

Pre-interv. variable	Sample HH (N=180)		PSNP HH (N=120)		Non-PSNP HH (N = 60)		Difference in		T
	Mean	STD	Mean	STD	Mean	STD	Mean	SE	
SEXHHH	0.94	0.22	0.95	0.21	0.93	0.25	0.016	0.036	-0.45
AGEHH	42.14	11.13	41.8	10.97	42.83	11.50	1.03	1.76	0.58
LITERHHH	1.68	0.69	1.6	0.61	1.85	0.81	0.25	0.10	2.29**
HHTARG	2.38	0.73	2.35	0.78	2.46	0.62	0.11	0.11	1.00
FAMSIZEHH	7.56	3.02	7.19	2.70	8.3	3.5	1.10	0.47	2.34**
HHACRED	0.5	0.50	0.52	0.50	0.45	0.50	-0.075	0.07	-0.94
HHIFERTUSE	0.75	0.43	0.78	0.41	0.7	0.46	0.08	0.068	-1.22
HHISDUSE	0.5	0.51	0.49	0.50	0.51	0.53	0.025	0.08	0.30
HHLDSIZE	1.36	0.89	1.09	0.65	1.59	1.17	0.50	0.13	3.66***
HHAEXSER	3.63	0.88	0.72	0.75	3.45	1.08	-0.27	0.13	-1.98**
DEPRHH	1.23	0.94	1.26	0.99	1.17	0.86	0.91	0.15	-0.61

*** and ** means significant at the 5 and 10% probability levels, respectively. AGEHH = Age of household head; LITERHHH = Literacy of household head; FAMSIZEHH = Family size of the household; HHTARG = Household targeted by the PSNP; HHACRED = target household's access to credit; HHIFETUSE = Household's inorganic fertilizer use; HHISDUSE = Household's use improved seed; HHLDSIZE = Household's farm land size; HHAEXSERV = Household's access to extension service; DEPRHH = Dependency ratio in the household.
Source: Own Survey Data (2023).

The data was computed from responses of PSNP beneficiaries for the last six years along with their comparative non-beneficiary households. The descriptive statistics focused on respondent characteristics. Descriptive statistics methods were used to analyze the performance of program implementation according to the program implementation manual and also to evaluate community asset development achievements. In this study, different descriptive statistics was used to analyze the household data. In Table 2, the means and standard deviations of sample households' characteristics are presented. Here, the analysis was carried out based on the households' pre-intervention characteristics.

The first set of data results were presented and analysed on the pre-intervention characteristics of sample households. As stated in Table 2, the descriptive results show that there were statistically significant differences between PSNP beneficiary and non-beneficiary households before intervention. The number of pre-intervention characters which show no statistically significant difference were sex, age, family size, dependency ratio, use of fertilizer and improved seed. This indicates that most households were in the similar demographic and technology use status before program intervention in the study area. The main differences between the two groups of households were observed with respect to land size, Literacy level and extension service before the intervention. Compared to non-beneficiary households, beneficiary households have smaller size of land, law level of education and have got better access to the extension service.

The analysis shows that, beneficiary respondents were less educated than non-beneficiaries. As indicated in Table 2, the beneficiary households were more illiterate than non-beneficiary households. These implies that due to their education status, non-beneficiaries were in better asset holding and entitlement level which made them to not be included in the program during targeting was carried out. Crop production requires primarily the availability of sustainable land. The total cultivated land of beneficiary and non-beneficiary households ranges from 0.13 to 4.5 ha. The land holding of beneficiary respondents ranges from 0.13 to 4.0 ha and non-beneficiaries ranges from 0.25 to 4.5 ha. Mean land holding of total respondents, beneficiaries and non-beneficiaries was 1.36, 1.09 and 1.59 ha, respectively. It indicates that the average land holding difference in between two groups is 0.5 ha. This indicates that, the average land size of beneficiary respondents was smaller than non-beneficiary groups. Large land size favored crop production of non-beneficiaries before program intervention which made them better-off during targeting. The analysis also declared that beneficiary households were more accessible to extension service than non-beneficiaries. The continuous contact to extension workers made the beneficiary group to be known as food insecure households since these development agents were constant members and main actors of the beneficiary targeting in PSNP implementation.

The second set of data results presented and analysed subsequently are the impact of PSNP on asset building (protection of household asset depletion from the droughts and related shocks). The PSNP intervention outcomes were classified into two categories for the purpose of this study. Household asset prevention and assurance of household food consumption were major outcomes studied and also of the program. Household asset prevention was measured by using four major outcomes namely, livestock holding, farm income, expenditure in housing and expenditure on farm tools and equipment. Assurance of food consumption of household was measured using outcomes: decrease in food insecure months, change in number of children meal per day, wage employment in peak farming season by adult members of family, and decrease in food transfer from relatives. The descriptive statistics analysis declared that as there is statistically significant difference in between beneficiary and non-beneficiary groups in three outcomes namely livestock holding, farm income, and expenditure in housing. According to the result, there is difference in expenditure on farm tools and equipment with mean difference of 70 birr but not statistically significant. It means that, beneficiary households expended more in farm tools and equipment even though it was not statistically significant.

The data in Table 3 presents descriptive statistics results of sample households based on their livestock holding, farm income, expenditure in housing, and equipment. The survey results show that program and non-program households had mean livestock holding of 4.09, 1.0 and 7 TLU with mean difference of 2.21 TLU, respectively. This means that households in the program are better off in livestock holding than those of non-beneficiaries. Expenditure in housing was significantly different in between two groups. According to the result of descriptive analysis, the mean expenditure of beneficiary households was 6375.83 and 2868.35 birr with mean difference of 3507.48 birr, respectively. This means, beneficiary households expended more money to improve their house and at the same time established their asset. The mean farm income of program and non-program respondents was 4539.12 and 1863.3 birr with mean difference of 2675.82 birr, respectively. This declares that farm income of the beneficiary households of the PSNP beneficiaries is more than non-beneficiary household. This implies that, the intervention of the program made difference in between two groups even though if requires further computation. In other hands the result of descriptive statistics indicated that there is difference in between two groups in terms of expenditure on farm tools and equipment. The computational result shows that beneficiary household expended more on buying farm tools and equipment even though it is not statistically significant. However, this descriptive result cannot tell us whether the observed difference is exclusively because of the program. Therefore, the program impact on asset prevention and food consumption outcomes was further analysed by using PSM econometrics model to detect the result whether it is exclusively due to the program intervention or not.

Inferential data results on the impact of the PSNP: The PSM estimation

The second part presents the Propensity Score Matching

Table 3. Contingency coefficient among discrete explanatory variables.

Variable	VIF	R2
AGEHH	1.36	0.0019
LITERHHH	1.43	0.0288
HHLDSIZE	1.07	0.0702
DEPRHH	1.00	0.0021

Source: Own Estimation Result (2023).

Table 4. Contingency coefficient among discrete explanatory variables.

Variable	Sex	FAMSIZE	TARG	CRED	FERTUSE	SDUSE	EXSER
SEXHHH	1	0.208	0.106	0.097	0.031	0.142	0.216
FAMSIZEHH		1	0.386	0.279	0.218	0.352	0.492
HHTARG			1	0.110	0.329	0.279	0.225
HHACRED				1	0.340	0.391	0.144
HHIFERTUSE					1	0.335	0.154
HHISDUSE						1	0.112
HHAEXSER							1

Source: Own Estimation Result (2023).

(PSM) results. The PSM estimate of the impacts of PSNP was conducted on two categorical variables: improvements in household food consumption and asset protection/building. Here, details how the propensity scores matching was estimated, presents the results of the common support region and the balancing test, and provides explanations on the treatment effect of PSNP participant households.

The results of a propensity score are obtained as the probability scores of individuals from the fitted simple logistic regression model. Logistic regression is applied when the dependent variable is dichotomous. The model is estimated with STATA 10 computing software using the propensity scores matching algorithm developed by Yibeltal (2008). In the estimation process, data from the two groups (PSNP participant households and non-participant households) were pooled such that the dependent variable takes a value of 1 if the household was a PSNP participant and 0 otherwise. Before running the regression model, the explanatory variables were checked for the existence of multicollinearity and heteroscedasticity. The VIF, as presented in Table 4, indicates the contingency coefficient and collinearity coefficient values of the variables in the model, showing that there is no problem of serious collinearity. To tackle the heteroscedasticity problem in the data, robust methods were used.

Table 4 shows the estimation results of the logit model. The logit model appears to perform well in estimating matching scores, with a pseudo-R-square value of 0.09. A low R-square value is desirable, indicating that program households do not have distinct characteristics overall, making finding a good match between program and non-program households easier (Yibeltal, 2008).

The estimated coefficients in Figure 1 and Table 5 show that, of the eleven explanatory variables, participation in PSNP was significantly influenced by three explanatory variables: literacy level of the household head, land holding, and extension service. As indicated in Table 6, the literacy level and size of land holding affected the outcomes of the PSNP negatively. Large land holdings and higher literacy levels were associated with non-participation in the program. The negative terms indicate that households with larger land sizes were not included in the program, and those with smaller land sizes were targeted. The literacy level of households included in the program was found to be lower than that of non-beneficiaries. Extension services positively and significantly influenced the targeting of beneficiaries.

The distribution of covariates between both groups should be systematically similar after matching. The common support region, as illustrated in Table 7, was imposed on the propensity score distributions of households with and without the PSNP intervention. The estimated propensity scores fell between 0.9066306 and 0.3074773 (mean = 0.71) for PSNP beneficiaries and between 0.8816158 and 0.087711 (mean = 0.56) for non-beneficiaries. The common support region was between 0.3074773 and 0.8816158, leading to the exclusion of one treatment household. Therefore, one treatment household was discarded. This shows that the study

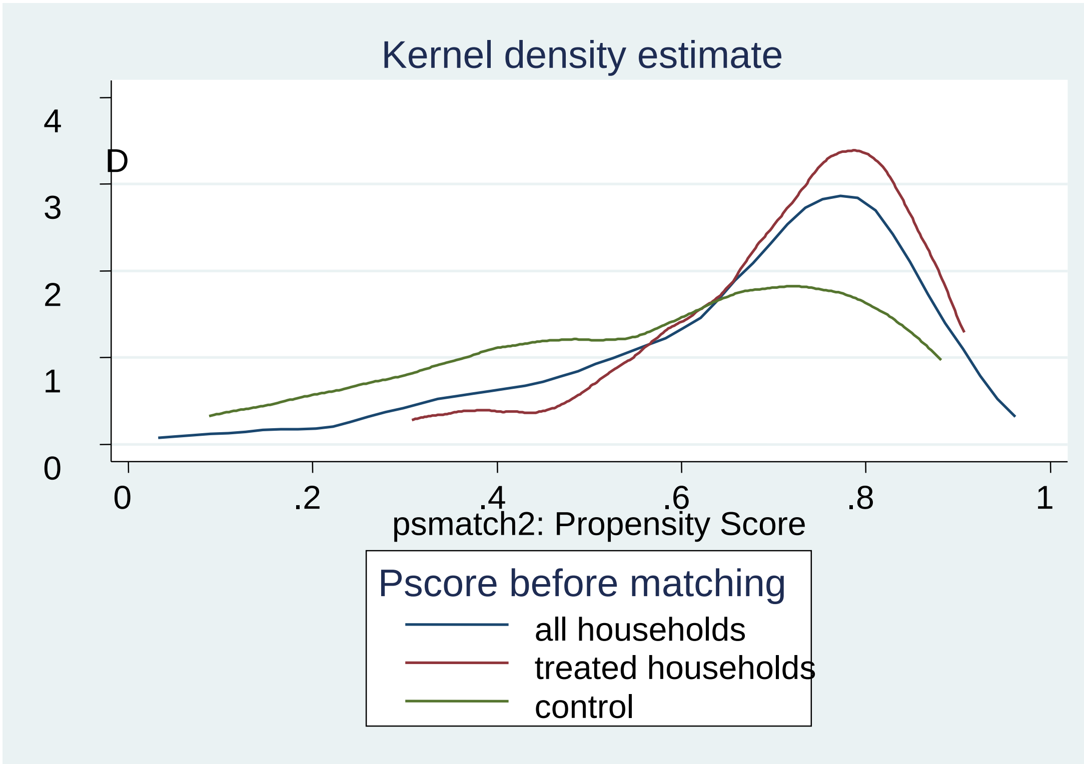

Figure 1. Kernel density of propensity scores

Table 5. Results of the logistic regression model.

Variable	Coef.	Robust Std.Err.	Z
SEXHHH	1.140388	0.8256221	1.38
LITERHHH	-0.7234534	0.3222893	-2.24**
FAMSIZEHH	-0.0988882	0.0673103	-1.32
HHTARG	0.0271462	0.2434719	0.11
HHACRED	0.1734162	0.399316	0.43
HHLDSIZE	-0.4807804	0.2066548	-2.33**
HHIFERTUSE	0.4662242	0.5178497	0.90
HHISDUSE	-0.0672806	0.3923967	-0.17
HHAEXTSER	0.285944	0.2025059	1.41
DEPRHH	0.1204276	0.1661363	0.72
cons	1.574166	1.747851	0.90

** and * means significant at the 5 and 10% probability levels, respectively. Sample size = 180; R = 20.11; LR X^2 (11) = 27.12; Prob> X^2 = 0.0044; Log likelihood = -101.37823.
Source: Own Estimation (2023).

Table 6. Distribution of sample households by estimated propensity scores and household type.

Group	Observations	Mean	Std Dev	Minimum	Maximum
Total households	180	0.6424764	0.17653985	0.087711	0.9066306
Treatment households	120	0.7150471	0.1365633	0.3074773	0.9066306
Control households	60	0.5699054	0.2145164	0.087711	0.8816158

Source: Own Estimation Result (2023).

Table 7. Comparison of the three matching estimates by performance criteria.

Matching estimator	Performance criteria		
NN Matches	**Balancing test***	**Pseudo R^2**	**Matched sample size**
1st neighbors	10	0.034	165
2nd neighbors	10	0.044	146
3rd neighbors	9	0.037	165
4th neighbors	10	0.032	165
Caliper matches			
0.01	10	0.049	146
0.25	11	0.026	165
0.5	10	0.048	65
KM matches			
With no band width	10	0.026	165
Band width of 0.1	10	0.024	165
Band width of 0.25	11	0.024	165
Band width of 0.5	10	0.048	165

*Number of explanatory variables with statistically no significant mean differences between the matched groups.
Source: Own Estimation Result (2023).

Table 8. Results of the balancing tests of covariates using the kernel matching.

Estimators	Before matching (180)			After matching (179)		
	Treatment N = 120	Control N = 60	T-value	Treatment N = 113	Control N = 52	T-value
SEXHHH	0.95	0.93333	0.46	0.9469	0.91362	0.98
AGEHHH	41.8	42.83	-0.59	41.86	42.31	-0.30
LITERHHH	1.6	1.85	-2.30**	1.6195	1.6244	-0.06
HHFAMSIZE	7.19	8.3	-2.34	7.32	7.37	-0.13
HHTARG	2.35	2.4667	-1.00	2.3805	2.4671	-0.92
HHACRED	.525	0.45	0.95	0.50442	0.41785	1.30
HHLDSIZE	1.0978	1.599	-3.66***	1.1381	1.0512	0.93
HHIFERTUSE	0.78333	0.70	1.22	0.76991	0.69519	1.27
HHISDUSE	0.49167	0.51667	-0.31	0.49558	0.46203	0.50
HHAEXTSER	3.725	3.45	1.98**	3.708	3.6157	0.82
DEPRHH	1.2641	1.1722	0.61	1.2333	1.2783	-0.39

***and** means significant at 1 and 5% probability levels.
Source: Own Estimation Result (2023).

does not have to drop many PSNP households from the sample in computing the impact estimator in Table 8. Table 9 presents the results of tests of matching quality based on the selected best estimator. Kernel matching with a band width of 0.25 was determined to be the best estimator for the data, as it matched more and had a lower pseudo-R-square with more statistically insignificant mean differences. After applying this matching technique, beneficiary and non-beneficiary households were found to be significantly similar in terms of certain pre-intervention characteristics (literacy level of the household head, land holding, and extension service). These differences were effectively removed through the matching process. The third issue presented and analyzed here concerns data results on the treatment effect on the treated regarding the assurance of food consumption status for both beneficiary and non-beneficiary households. This part is further categorized into four outcome variables: a decrease in months of food insecurity, changes in the number of children's meals per day, wage/jobs in peak farming season, and changes in food transfer from relatives.

Table 9. Average treatment effect on the treated (ATT) for food consumption outcomes.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
TLU	ATT	0.292035	0.358477	0.066442	.083832	-0.79
HHEXPH	ATT	1.2389	1.7398	-.5009	0.138295	-3.62***
HHEXPEQ	ATT	0.7522123	0.4535271	0.29868524	0.085904	3.48***
TOTALFI	ATT	1.787610	2.9265282	-1.13891758	0.181205	-6.29***

*** and ** means significant at 1 and 5% probability level.
Source: Own estimation result.

Table 10. Average treatment effect on the treated (ATT) for food consumption outcomes.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
TLU	ATT	4.12	1.56	2.56	0.2782	9.22***
HHEXPH	ATT	6434.51	3439.16	2995.34	1289.63	2.32***
HHEXPEQ	ATT	1925.90	1283.60	642.29	445.24	1.44
TOTALFI	ATT	4730.48	1484.48	3246.00	658.39	-4.93***

*** means significant at 1% probability level.
Source: Own Estimation Result (2023).

Decrease in months of food insecurity

The estimation results in Table 10 provide supportive day in beneficiary households compared to non-beneficiary households. The analysis shows a statistically significant difference between the two groups at the 1% probability level.

Wage employment in peak farming season

The statistical estimation results demonstrate that wage employment during the peak farming season was influenced by the program intervention. The mean difference between the two groups was 0.06, indicating a decrease in beneficiary household participation in wage employment during the peak farming season, although not statistically significant. Overall, the PSNP intervention increased children's meals per day, decreased food insecure months, and reduced food transfer from relatives, ensuring food consumption.

The fourth issue presented and analyzed here focuses on the treatment effect on the treated groups regarding the PSNP outcomes on preventing asset depletion in shock contexts by households. The second objective of the PSNP intervention was to prevent the assets of food-insecure households. The estimation results presented in Table 10 provide evidence of a statistically significant effect of the program on household asset prevention, measured in tropical livestock units (TLU), expenditure in house improvement, total farm income, and expenditure in farm tools and equipment.

Livestock holding

The mean difference in livestock holding between beneficiary and non-beneficiary households was 2.56 TLU, showing a statistically significant difference. On average, the PSNP intervention increased the livestock holding of beneficiary households by 2.56 TLU (Table 10).

Total farm income

There is a statistically significant difference in total farm income between treatment and control groups. The average total farm income of beneficiary households was significantly higher than that of non-beneficiary households, indicating a positive impact of the PSNP intervention.

Expenditure on housing

The outcome variable of expenditure on housing showed a statistically significant difference between participant and non-participant respondents of the program. The average expenditure to improve the houses of beneficiary households was significantly higher, indicating the positive effect of the PSNP intervention.

Expenditure on farm tools and equipment

Although not statistically significant, the PSNP intervention showed an increase in the expenditure on farm tools and equipment on average by 642.29 Ethiopian birr.

The outcome variables related to household asset prevention demonstrate that the PSNP intervention not only prevented but also increased the assets of beneficiary households.

DISCUSSION

First, from the PSM results, the PSNP improved the smoothening of food consumption of the beneficiary households. Previous studies support this finding (Coll-Black et al., 2011; Abraham, 2020; Andualem, 2020; Bahru et al., 2021; Hailu and Amare, 2022; Feyisa, 2022; Guush et al., 2017b; Abdi et al., 2023). As expected, the participation of the beneficiary households in the PSNP was determined by a combination of demographic, socio-economic, technological, vulnerability and institutional factors; and this finding was also consistent with the findings of Ahmed and Burhan (2018). Treatment households were more likely to have smaller land size, more illiterate than control households and were in better contact with extension agents. Finding a reliable estimate of the PSNP impact thus necessitates controlling for all such factors adequately. A study by Paulos and Melese (2018) also found similar results.

After controlling for other characteristics, it was been found that PSNP intervention had significantly increased children meal per day, decreased food insecure months and decreased food transfer from relatives. Though the decrease in wage employment during peak farming season was not statistically significant, there was change due to the intervention. More particularly, the PSNP assured beneficiary households food consumption. Therefore, the PSNP decreased food insecure months and significantly improved the household's capacity to respond to shock burdens.

Second, from the PSM results, the PSNP had impact on prevention of household assets from depleting. This finding was consistent with the empirical evidence documented by Gashaw and Seid (2019), Zerhun (2020), Abdulhakim et al. (2022) and Tareke (2022). The PSNP intervention had significantly increased livestock holding, entitlement to cash/food vouchers, farm income and increased spending on house refurbishment. Anderson et al. (2009) also found the same result by their study conducted by in Ethiopia. Even though the increase was not statistically significant, there was increase in investment on farm tools due to PSNP intervention. More particularly, PSNP intervention prevented household asset from depletion and increased asset holding of program beneficiaries significantly. Thus, the PSNP increased household assets.

There were constraints in the PSNP implementation, and thus, the achievements were not as expected. This finding was consistent with the empirical evidence documented by Addisalem et al. (2023). The PSNP intervention succeeded in establishing infrastructures such as basic rural access road and rehabilitation of communal lands. Farmers training centres, primary schools, health posts, spring development and water shed management practices were implemented by food and/or cash for work, and was implemented per the program implementation manual and the objective of the project. However, there were delays in resource transfers, targeting and limited in time/geography.

PSNP was required to smoothen food consumption and prevent asset depletion. Whereas other complementary programs were basic to develop asset of the household in order to build household's capacity to buffer shocks, and recover from shock impacts. This finding is consistent with the work of Andersson et al. (2009), Gelebo (2010) in Konso, South Ethiopia, Guush et al. (2017b) in north Ethiopia and Tasew and Tariku (2022) in Central Ethiopia. In this respect, ninety (7%) of the households that participated in program responded that the change to their asset status was due to the benefits they got from the PSNP. The program support made the beneficiaries to move on the track of stability in the context of recurrent shocks, and their assets were not depleted to critical level. In general, the program was implemented significantly as planned. Precisely targeting of beneficiaries and integrating the program with other development programs, such as environmental rehabilitation and social protection for labor poor families, improved the achievement of the PSNP. Though the resource transfer requires timely and tailored targeting, both the food and cash vouchers enhanced the capacity of the beneficiary households to: (1) respond to shocks on time before its hazard impact gets critical in affecting crops and livestock, and (2) enhanced the transferability of financial (cash) assets to other forms of assets and enlarged the preferences of diverse categories of poor households in the shock context. The findings are consistent with the empirical evidence documented by Emerta et al. (2020), Fantu and Minten (2021, 2023) and Addisalem et al. (2023)

Conclusions

In this study, cross sectional data from Southern Ethiopia were used to evaluate the impacts of PSNP on household asset prevention, food consumption assurance, community asset development and to identify constraints in implementing the program. The main question that this research attempted to answer was "what would the food consumption, asset prevention and protection status of households if they were not engaged in PSNP?" Answering this question requires observing outcomes with-and-without participation in PSNP for the same household. However, it is impossible to observe the same object in two states simultaneously. To assess the impact of program intervention, it requires base line data to take pre intervention as control and intervention as treatment group with in the same household but there was no intended data.

This study used descriptive statistics to analyze the community asset development and to identify the constraints in program implementation. The PSM technique was used to evaluate the *PSNP* impact in asset prevention and food consumption of households to eliminate the possible sample selection bias since the data were from a survey study. To overcome this beneficiary and non-beneficiary selected as a sample respondent from survey kebele's assuming they were under the same situation before the program intervention.

The primary data for this study was collected from 180 beneficiary and non-beneficiary households in the same kebele's and a structured questionnaire was administered to the study. The availability of baseline data was examined, and found that baseline data were not available. The study emphasized; selection bias is to be expected in comparing a sample from the population of PSNP beneficiaries with a sample of non-beneficiaries. To pin out the outcome exclusively due to program intervention, simply comparing by using descriptive statistics can make bias. Every micro econometric evaluation study has to overcome the fundamental evaluation problem and address the possible occurrence of selection bias. The first problem arises because we would like to know the difference between the participants' outcome with and without treatment. Clearly, we cannot observe both outcomes for the same individual at the same time. Taking the mean outcome of non-participants as an approximation is not advisable, since participants and non-participants usually differ even in the absence of treatment (Caliendo et al., 2008). In both cases, issues such as self-selection and endogeneity of program placement would create serious problems when using these kinds of impact evaluation exercise. Hence, the study has applied a PSM technique, which is capable of extracting comparable pair of treatment-comparison households in a non-random program setup and absence of baseline data (Dehejia and Wahba, 2002).

RECOMMENDATIONS AND AREAS OF FUTURE RESEARCH

PSNP is important development efforts to ensure food security at household level if implemented properly. Based on the empirical findings reported in this thesis, the following policy recommendations are forwarded.

1. Regional executive bodies could maximize livelihood options by maximizing intervention packages. The study finding indicates that those beneficiary households participated in HABP were better used the PSNP intervention to increase their assets and assure their food consumption even the participation in program years was not more than 58%. The annual inclusion of PSNP beneficiaries in HABP should increase to fasten graduation of beneficiaries from PSNP and food security programs.
2. Most beneficiary households cannot read and write which has negative relation with technology adoption and graduation from both PSNP and FSP. In other words, adult education is important for technology transformation. In this context a means to tackle illiteracy should be designed.
3. Most beneficiary households land holding is very small which cannot afford large family size even though the productivity of land per unit area increases to the maximum. It is better to look for open cultivable land in the Woreda and also in the resettlement areas for households with less than 0.5ha holdings.
4. Excluded family members from the program should be included to fasten the graduation of beneficiaries from both programs by excluding better off family members. In other hands, resource transfer should be timely to protect asset of the beneficiary households.
5. Further research at broader regional and country level is required to generalize the impact of PSNP on household food security (consumption) and asset building (prevention of household assets from depletion).

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CONFLICT OF INTERESTS

The author has not declared any conflict of interests.

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