Impacts of Agricultural Rehabilitation Program in Bangladesh: A Propensity Score Matching Analysis

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Abstract:

The objective of the study is to identify the productive outcomes of agricultural rehabilitation program (ARP) at household level in Bangladesh. The study used latest Household Income and Expenditure Survey, 2010 and have applied PSM approach to analyse the impacts. The study has chosen 4286 households to include in probit model as control group from the households other than the treated group of 446 households. Propensity scores ranged from approximately zero to one with a mean of 0.102. Various indicators such as labor allocation, income generating activities, investment and shock`s coping strategies etc. were chosen to identify the productive outcomes. The ATE on the treated was significant for income generating activities (farm and non-farm), labor allocation (farm and non-farm, self-employment) and investment (agricultural assets, inputs). The farm activities increased by 0.40 units but non-farm activities declined by 0.73 units per household due to agriculture rehabilitation program. One of the areas of reduction of labor unit is day laborer in non-farm sector - moved from non-farm to on-farm activities. The results suggest that ARP is a promising means of safety net for the marginal and small farmers in Bangladesh. This type of safety net could contribute more to productive outcomes.

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Key words: Agricultural rehabilitation program, propensity score matching, Bangladesh

1. Introduction

Agriculture is the largest sector of the Bangladesh economy contributing about 15.16 percent of the Gross Domestic Product and about 60 percent of the total labour force is employed in agriculture (BBS, 2015). From being a major importer of food, Bangladesh in the last few years was more or less self-sufficient in food production. However, almost every year the country has suffered from a series of disasters, such as flash flood and cyclone which in one hand disrupted the agricultural productivity and reduced crop yields drastically and in other hand also adversely disrupting the livelihood of small and marginal farmers whose lives are depending completely on agriculture. This is happening almost in every year in the southern and coastal regions of the country. Due to the high incidence of shocks small and marginal farmers are belong in or below the poverty line and if this continues, achieving the goals of sustainable development will remain a dream.

Like many other developing countries, social safety net programs (SSNPs) in Bangladesh can play a vital role to reduce poverty through direct or indirect incentive to small and marginal farmers especially in the periods when they are in serious need. According to Household Income and Expenditure Survey (HIES 2010), there are 30 public SSNPs in the country - 10 are conditional, eight unconditional, five are credit schemes and three are conditional subsidy programs. Of these 30 SSNPs Agriculture Rehabilitation Program (ARP) program directly linked with agriculture. Under this program government provides agriculture inputs to marginal cardholding farmers who were affected by flash floods or natural calamities at free of cost to encourage them to produce more food grains and to help them to reduce their sufferings during any natural disaster. Therefore, this program is designed to rehabilitate the small and marginal farmers' and provide them agricultural inputs such as seeds, fertilizers and farm machineries etc., through Directorate of Agricultural Extension, government of the peoples republic Bangladesh after natural disaster.

In the country, a good number of studies investigated targeting, delivery mechanism, operational performance, alternative design, impact assessment etc., of different SSNPs in Bangladesh. (Ahmed, 2004; World Bank, 2006; Morshed, 2009; Ahmed et al., 2007; Khandker et at. 2011) but no study explored the productive outcomes of SSNPs particularly for the program which is directly related with agricultural sector. Given the above backdrop, the objective of this paper is to estimate the household level`s productive impact of ARP in Bangladesh. This research, by identifying the productive outcomes of ARP will provide the policy makers ground level information and recommendations that will frame the design of more effective and efficient ARP.

The paper is organized as follows. Following introduction, research methodology is presented in section 2. The results and discussions are presented in section 3. Last section presents the conclusions and policy recommendation.

2. Methodology

Analytical framework

Application of the propensity score matching (PSM) approach is appropriate to analyze the impact of Agricultural Rehabilitation Program (ARP) on productive outcome. The hypothesis tested is whether ARP facilitates significant changes in productive outcome of beneficiary households than non-beneficiary households. Specifically, the hypotheses tested are whether agriculture rehabilitation program expedite significant changes in income generating activities, farm and non-farm labour allocation, productive assets accumulation and investments of beneficiary households than non-beneficiary households. The research questions are what are the productive outcomes of agriculture rehabilitation program at the household level? Sub research questions are what are the impacts of ARP on labour allocation, can ARP beneficiaries use the SSN supports to productive investment, how does the ARP fund affects beneficiaries' income generating activities, what are the effects on detrimental risk coping strategies, such as distress sales of productive assets.

The objective of an impact assessment is to attribute an observed impact to the social safety net program that is ARP intervention. The identification of the counterfactual is the organizing principle of an impact assessment. However, methodological care is necessary because ‘what would have happened without the selected ARP intervention’ is unknown (this is known as counterfactual). We must compare the observed outcome due to the agricultural rehabilitation program with the outcome that would have resulted had the households not received ARP benefits. In reality we observe only one outcome, which is known as factual outcome. The counterfactual outcome, which we do not observe is the one which would have resulted had the benefit receiving households, not received it. The challenge is to estimate the counterfactual in a reliable way. In this study to assess the impact of social safety net intervention on productive outcome we used propensity score matching method. The advantage of propensity score matching (PSM) model is that this approach do not necessarily require a baseline or panel survey (especially for the outcome variables) although the observed covariates entering the probit model for the propensity score would have to satisfy the conditional mean independence assumption by reflecting observed characteristics that are not affected by participation.

Impact is the difference between actual outcome and the outcome would have happened without intervention. Counterfactual outcome is the unknown outcome, which would have happened without intervention. In HIES 2010 data we observe what has happened with ARP intervention, but we need to estimate what outcome would have happened without intervention. To take care of this counterfactual problem we require an appropriate analytical technique.

We have chosen matching approach as HIES data are not experimental but sufficiently large and rich. Formally, average impact of program intervention could be expressed as follows (Rubin 1974, Ravallion 2008):

$$\bar{I} = \frac{1}{n}\sum_{i=1}^{n}(Y_i^T - Y_i^C) \tag{1}$$

Where I is `impact`, Y is the value of the interpretable impact indicator, T and C represent treatment group and control (comparison or non-treated) group respectively, i represents the sample units and n is the sample size. In randomized control trials (RCTs) or experimental data, the mean I is an unbiased estimator of the true impact. The true impact is unknown, because one of Y^T and Y^C remains unknown at the time of evaluation being done (Dehjia and Wahba, 2002). In RCTS, randomization ensures that, on average, treated subjects will not differ systematically from untreated subjects in both measured and unmeasured baseline characteristics (Austin, 2009). Non-randomized or non-experimental studies of the effect of treatment on outcomes can be subject to treatment-selection bias in which treated subjects differ systematically from untreated subjects. Impact would be biased in non-experimental data like HIES 2010. To elaborate the phenomenon, we may use the following equation:

$$E\,(I|X) = E\,(Y_i^T - Y_i^C|X) = E\,(Y_i^T|X, T) - E\,(Y_i^C|X, C) \qquad (2)$$

Where X is a vector of the covariates, E refers to expected values. This program impact is generally referred to as the `average impact of the treatment on the treated` (ATT).

Without matching groups (treated and control) there are two sources of bias in ATT (difference between the true average impact and estimated average impact) in non-experimental data (Heckman et al., 1998). First, bias is due to the difference in the supports of X covariates in the treated and control groups and the bias due to the difference between the two groups in the distribution of *X* over its common support. Matching methods are able to reduce the bias reasonably by avoiding potential misspecification when estimating counterfactual. It also allows for arbitrary heterogeneity in causal effects. Rosenbaum and Rubin (1983) proposed propensity score matching (PSM) as a method to reduce the bias in the estimation of intervention impact. The approach identifies a matching untreated control group for the intervention group (treated group) using estimated propensity scores (PS). The

PS is defined as the probability that a household would participate in the program given a set of variables (observable characteristics). The objective of PSM is to re-create the condition of a randomized control trial or an experimental trial.

Alternative to PSM is regression analysis. PSM is preferable because it does not require distributional assumptions, which are required in regression analysis. Also, PSM is a non-parametric approach in which the functional relationship between the dependent and independent variables does not need to be specified. PSM on observables also ensures that treated and untreated households are comparable on observable variables, something that is not guaranteed in the regression analysis. Rubin (2001) argues that an advantage to the use of PSM is that it allows observational studies to be designed similar to randomized experiments: the design of the study is separated from the analysis of the effect of exposure on the outcome.

PSM requires conditional independence assumption (CIA) and common support or overlap condition. The variables chosen in the PS models are based on socioeconomic factors affecting participation in the program and may influence outcome but not the other way round. This is the requirement of CIA, which means that conditional on the observable variables included in the PS models (probit or logit models), the outcome variables are independent of treatment. That is, outcomes between control group and treatment group would be the same without a SSNP intervention. The variables, which would satisfy CIA, should be included in the analysis. PSM also requires common support or overlap condition, which means that households are either treated or non-treated with certainty.

From the estimated PS and matching we can analyze data from households with the statistically same value for the X covariates, as if completely randomized experiment was carried out. Different matching algorithms are available to match household with the estimated PS. These matching methods are Nearest Neighbor Matching, Stratification and

Interval Matching, Caliper and Radius Matching and Kernel Matching among others. Asymptotically, all matching methods should yield the same results. However, in practice, there are trade-offs in terms of bias and efficiency with each method (Caliendo and Kopeinig, 2008). The basic approach is to numerically search for `neighbors` of non-participants that have a propensity score that is very close to the propensity score of the participants. However, we have employed Nearest Neighbor Matching (NNM), the most straightforward method of matching, to form pairs of treated and untreated households. However, we carry out sensitivity analysis using few other algorithms such as Caliper Matching, Radius Matching and Kernel Matching. The NNM selects households in the control group as matching partners for beneficiaries, on the basis of the closest propensity scores (Abadie et al., 2004; Abadie and Imbens 2006; Gilligan et al., 2008). Following this approach, the treated and the control groups are matched in a way that households included are very similar to each other except for the participation to the program. However, NNM matches directly on the variables themselves by selecting non-beneficiaries for the match that minimize the average difference in characteristics from the beneficiary using a multidimensional metric to determine the weights for constructing the average. A strength of NNM matching approaches is that it can provide reliable estimates of program impact provided that (i) a comparable group of non-beneficiary households in available, and (ii) there is access to carefully collected household survey data with many variables that are correlated with program participation and the outcome variables. The PSNP sample was designed to include an appropriate comparison group.

Commonly, probit or logit models are applied to estimate PSs. We use probit model in this study. In general, the choice of variables to insert in the propensity score model should be based on theory and previous empirical findings. As the true PS is unknown, residual systematic differences between treated and untreated subjects may be reduced by improving the specification of the propensity-score model (Austin, 2009). We adopt parsimony to choose final variables based on the percent of bias arising from each of the variables and balancing property. The bias is defined as the difference of the mean values of the treatment group and the (not matched/matched) non-treatment group, divided by the square root of the average sample variance in the treatment group and the not matched non-treatment group.

However, the steps of using PSM are as follows. (a). Outcome variables and covariates (X elements from the HIES 2010) are selected. X covariates would satisfy assumption of conditional independence. (b). Applying probit regression to estimate P(X) and the probability of being treated excluding the households not stratifying the common support or overlapping condition and, (c). Estimating an average treatment effect.

Data Sources and Sampling

The main data source for this study is the HIES, 2010. This household survey was carried out by the Bangladesh Bureau of Statistics (BBS) from February 2010 to January 2011. The sample in the HIES-2010 survey was selected using a two-stage stratified random sampling design technique under the integrated multipurpose sample (IMPS) design framework developed on the basis of the 2001 population census. The sample comprised 612 primary sampling units (PSUs) throughout the country, whereas 164 PSUs in urban areas, 392 PSUs in rural areas and 56 PSUs in small metropolitan areas (SMA). The PSU was defined as contiguous two or more enumeration areas used in population and housing census 2001. This PSUs were selected from 16 different strata, where 6 rural, 6 urban and 4 SMAs. At the first stage, about one half, 612 is in exact out of total 1000 IMPS-PSUs were drawn. At the second stage, 20 households were randomly selected from each of the selected PSU. Total sample size of the survey was 12,240 households, where 7,840 households from rural area and 4,400 from urban area. HIES 2010 includes data on age, sex, marital status, religion/ethnicity, education, housing, income and expenditure, consumption, employment, health, basic service (water, sanitation and electricity etc.) assets description and social safety nets. The SSNP module was first introduced in HIES 2005 in which 11 programs were included but its scope has been widened to include 30 SSN programs in HIES 2010. For estimating the productive impact of ARP at household level the HIES repeated cross sections i. e., HIES 2005 and 2010 data is not appropriate. HIES 2005 and 2010 is not a true panel, thus, same household is not included in the two different surveys. Apart from that, it is not possible to identify the similar household because of the dynamics associated with household in and out in the safety net programs. Therefore, in this study, we used HIES 2010 as a single cross section data for identifying the treatment (beneficiaries) and control (non-beneficiaries) groups for estimating the productive outcomes of ARP using PSM approach.

The main data source for this study is the Household Income and Expenditure Survey 2010 (HIES, 2010). HIES 2010 includes not only data on income and expenditure, but also includes several other modules on topics such as education, housing, employment, health, assets and social safety nets. The SSNP module was first introduced in HIES 2005 in which 11 programs were reported. However, in HIES 2010 its` scope has been widened to include 30 programs. ARP is one of program of these 30 programs.

Table 1: Participant and non-participant of SSNPs in HIES 2010

Has benefitted from social safety nets?	No. of individuals	Percent
Benefited from SSNPs	3508	6.3
Not benefited from SSNPs	46428	83.5
No answer/not applicable	5644	10.2
Total	55580	100.0

Source: Authors` calculation based on HIES, 2010

However, the study have identified the household having benefits from only ARP program because our interest is to measure this program's impacts, so no overlapping is considered.

Only 6.3 percent of population (i.e., 3508 out of 55580) was included in SSN programs who are considering as participants and rest 93.7 percent (52073) are considering as non-participants (Table 1). Out of this 3508 beneficiary ARP beneficiary are only 560, which is 16% of total SSNPs beneficiary (Table 2). Respondent (non-participant) of HIES 2010 were also asked reasons for not included in SSN programs. However, the study consider the respondents who stated that they didn't know about the program or they were fit for the program but not apply or they excluded due to shortness of budget or they stated selection procedure was not proper or if stated no SSNP in the area are as control group. The distribution of causes of not being included in major SSNPs is presented in Table 3.

Table 2: Number and percent of beneficiaries of ARP in HIES 2010

SSNP	Beneficiaries (National)	No. of beneficiaries	Percent
Agriculture Rehabilitation	250000	560	16.0
Total		3508	100.0

Source: Authors` calculation based on HIES, 2010

Table 3: Distribution of causes of not being included in major SSNPs

Reasons for not included in SSN programs	Frequency	Percent
No answer (beneficiary and HH member age< 5 years)	9138	16.4
Didn't know about the program	2045	3.7
Not fit for that program	29939	53.9
Fit for the program but not apply	1853	3.3
Due to shortness of budget	1769	3.2
Selection was not proper	9975	17.9
No program in this area	861	1.5
Total	55580	100.0

Source: Authors` calculation based on HIES, 2010

The study further disaggregates the beneficiaries by the AR programs. After preliminary assessment of HIES 2010 data, found that about 29 percent of households were participating in two or more SSNPs. This point to a need to specify program impact and target beneficiaries more clearly, to avoid overlaps in treatment groups, and to minimize the number of households capturing benefits from multiple programs, so, single program beneficiary are selected as sample. Therefore, 560 participants have benefited from AR program, out of 560 participants, 114 participants benefited from ARP along with at least one of other 29 SSNPs, so we deduct this 114 from 560 participants and found 446 single beneficiaries for the sample of this selected SSNP (Table 4). Finally for PSM analysis of the ARP, we consider to use 446 participants as treatment group.

Table 4: Number of beneficiary household of agriculture rehabilitation in HIES 2010

Programs beneficiary Households	Included number of households benefited by multiple SNPs	Beneficiary of single SNP
560	114	446

Source: Authors` calculation based on HIES, 2010

Finally, the study has chosen 4286 households to include in the probit model as probable control group from the households other than the treated group of 446 households. These 446 households were not benefitting from any other programs but the ARP.

3. Results and Discussions

Estimation procedure of productive outcome at household level

The productive outcomes of ARP at the household level chosen for analysis are (i) changes in labour allocation/employment, (ii) income generating activities, (iii) investments in land, tools, animals, family enterprises, durable goods and housing improvements, and (iv) changes in coping mechanisms. A list of measurable outcome indicators which are derived from HIES 2010 are presented in Table 5. We considered a broad set of outcomes. Thematically, these are divided into four categories:

Labour allocation: There is a debate surrounding safety net is whether SSNP intervention reduces work effort. In this connection we focus on selecting specific indicators to assess labor allocation. One of the evaluation question in this respect is whether SSNP intervention increases labour participation in both farm and non-farm sectors. We have used average working hours per day per worker in farm and non-farm activities as outcome indicators to measure the impact.

Income generating activities: A persistent concern in policy debates adjacent safety nets is whether their provision reduces work effort in other income-generating activities. Therefore, income generating activities are also addressed in this set of outcomes. Income generating activities are assessed by number of total activities per household per active member, total farm income (crop, vegetables, livestock and fishery), total non-farm income (small business, cottage) etc.

Investment: Household investment indicators assess whether the SSNP intervention increase or changes in the value of farm assets, new land purchased, agricultural Expenditure increased and increased in durable goods and housing improvement. The study used household expenditure on tools, animals, family enterprises, expenditure on tools, animals, family enterprises, durable goods & housing improvements per person, convert into real terms.

Shock and coping indicators: Shock and coping indicators includes per capita consumption, distressed sale, migration, school dropout etc. Per capita consumption is a useful summary measure of household welfare and shock coping. Variation in this indicator is easier to measure than income and less subject to short-term economic effects. As such, it provides a better reflection of differences in permanent income. Not only is household consumption expenditure a useful indicator in its own right, improvements in this outcome may contribute to the objective of promoting market development by increasing household purchasing power. Insurance, migration and school dropout are measured as dummy variables. These indicators are related to shocks and coping mechanism.

Table 5: Measurable productive outcome indicators at household level

Outcomes	**Indicator**	**Measurable indicator**	**Imputed from 2010 HIES**
Labour allocation	Relative farm employment	Average working hours per day per worker in farm activities	Calculating daily male and female hours in farm activities
	Relative non-farm employment	Average working hours per day per worker in non-farm activities	Calculating daily male and female hours in non-farm activities
Income generating activities	Total no. of activities involved	Number of total activities per household per active member	Calculate total number of activities for each active members of the household add them to obtain the total for each household
	Total farm income	Per household	Calculating total farm income (crop, vegetables, livestock and fishery)
	Total non-farm income	Per household	Calculating total non-farm income (small business, cottage)
Investments	Land purchased	Dummy variable: if land purchased =1	
	Agricultural Expenditure per household	Real expenditure on tools, animals, family enterprises per household	Calculate household expenditure on tools, animals, family enterprises, & convert into real terms
	Real	Real expenditure on	Calculate household

	expenditure on durable goods & housing improvement	durable goods & housing improvements per person (may be separate variable for the highlighted things)	expenditure on tools, animals, family enterprises, durable goods & housing improvements per person, convert into real terms
Shock and coping mechanism	Asset sold	Dummy variable: if assets sold due to shock =1	
	Per capita consumption	Sum of per capita value of food and non-food expenditures. As it is expected households cope better in shock due to SSN so the variability in per capita food consumption would be lower for beneficiary group. Thus per capita food consumption expenditure due to shock considered as indicator variables.	Food expenditures are based on reports of the consumption of 33 different foods in the 14 days prior to the interview from purchases, stocks and amounts received as gifts, barter or in-kind payments. These quantities were converted to values using household self-reports of purchases. Non-food expenditures include purchases of fuel and lighting, cosmetics and other expenses, washing and cleaning expenses, transport/ travel and other misc. charges, ready-made garments, clothing material and tailoring, footwear, medical treatment expenses, housing related expenses etc.

This section analysed the household income and expenditure survey (HIES) 2010 data to investigate the impact of selected social safety nets on productive outcomes at the household level. HIES is a large data set that contains safety net module. Using this type of non-experimental data set for impact assessment poses challenge of estimating counterfactual outcome. HIES (2010) survey included 12240 households. In the data the participant households in the AR programs were 446. These households were not benefitting from any other programs but the selected program, one household in one type only.

The primary inclusion criterion for ARP is farmers must have operated land and farmers are belongs to small and marginal farm category (0.05 – 2.49 acre). We have chosen 3840 households to include in the probit model as probable control group from the households other than the treated group of 446 households.

Variables in PS estimation

The variables to be included in PS estimation are depicted in Table 6. The dichotomous dependent variable is the dummy variable representing program participation (treated=1). Some of the exogenous X covariates for probit models correspond to targeting criteria of the SSNPs. So, the study have chosen the variables age, gender, education of household head, characteristics of the house (number of people per rooms), own land etc., which are taken into account whilst participants are chosen in the ARP as a government safety net program. Two thirds of the 22 exogenous variables listed in Table 6 have higher standard deviation than mean showing wide variations.

Table 6: Observable characteristics included as dependent & independent variables

Variables	**Description**	**Mean**	**Standard Deviation**
Dependent variable			
Dummy	Dummy variables (Treated=1)	0.63	13.49
Independent variables			
AgeH	Age of household head (years)	46.14	14.26
EduH	Education of household head (years of schooling	2.78	3.96

EduHD	Household head is illiterate=1	0.62	0.49
Land	Owned land (decimal)	35.87	92.66
LandO	Operated land (decimal) (land+lease in – lease out)	54.45	107.11
FishD	Dummy variable (Income from fish=1)	0.15	0.36
FamS	Total household size	4.48	1.83
Chl514	No of Children 5-14 years	1.12	1.08
Male65	No of Male 65+ year old	0.12	0.33
Female62	No of Female 62+ year	0.15	0.36
FemaleP	Female % in household	52.03	19.28
Disable	Member disable=1	0.12	0.33
Deprat	Dependency ratio	82.68	70.26
DayL	At least a member work as day labor=1	0.03	0.18
mstatF	Women currently unmarried, separated, divorced etc. =1	0.21	0.40
Elect	Electricity connection=1	0.24	0.43
Room	Room per person in household	0.48	0.50
Landless	Dummy variable (landless=1)	0.66	0.47
Homeless	Dummy variable (homeless=1)	0.10	0.30
R1	Regional dummy (Rural=1)	0.69	0.46
R2	Regional dummy (Urban municipality=1)	0.22	0.42
R4	Regional dummy (Urban SMA=1)	0.08	0.27

Regional dummies are included to account for rural and urban specific factors affecting selection for participation in the programs.

The study used these variables as well as higher order variables of age and education to identify the best specified probit models based on balancing properties. The study started with all the variables in Table 6 plus higher orders of age and education variables and so in total we included 24 covariates. Then the study excluded the variables which have the statistically the same mean values between treated and control groups before matching. The criteria for variable selection are thus likelihood ratio test, Pseudo R^2, mean and median bias. Pseudo R^2 indicates how well X covariates explain the participation probability. In this study the sample size was 4286 including 446 treated households. We use PSmatch2 in STATA to do the analysis.

The balancing properties of the characteristics variables are shown in Table 7. This shows that the control household are matched closely with the beneficiary households by the method of nearest neighbour matching. Probit scores were estimated using 17 characteristics variables from the list in Table 7. Three variables including land were excluded but higher orders of age and education variables were included in the model based on their balancing properties. We haven't shown the probit results because the model for the propensity scores does not need a behavioral interpretation. The estimated PS ranged from 0.003 to 0.33 with an average of 0.10.

The t-test in the Table is on the hypothesis that the average value of each variable is the same in the treatment group and the control group. The test was performed both before and after the matching. Group averages are statistically the same after matching; the null hypothesis cannot be rejected at the 1 percent level of significance. All average values were highly significant before matching.

Table 7: Indicators of covariate balancing by variable, ARP, 2010

Variable	Description	Treated	Control after matching	% bias after matching	p>t after matching
ageH	Household head’s age in years	48.34	48.75	-0.45	0.65
ageh2	Household head’s age in square term	2518.60	2559.10	-0.44	0.66
ageh3	Household head’s age in cubic term	140000	140000	-0.42	0.68
eduH	Years of schooling of household head	3.26	2.74	1.91	0.06
eduh2	Schooling square of head	28.21	22.22	2.21	0.03

eduHd	Dummy variable (head illiterate=1)	0.57	0.62	-1.36	0.17
famS	Family size (no of persons)	4.67	4.61	0.46	0.65
femaleP	Female percent in household	47.85	47.71	0.12	0.91
chl514	Children no. (from age 5 to 14)	1.03	0.99	0.63	0.53
female62	Female no (age 62 and above)	0.13	0.13	0.29	0.77
male65	Male no. (age 65 and above)	0.13	0.13	0.10	0.92
disable	Member disable=1	0.00	0.00	0.58	0.56
mstatw	Women currently married =1	0.14	0.14	0.00	1.00
elect	Electricity connection=1	0.50	0.46	1.14	0.26
roomsPC	Room per person in household	0.53	0.55	-1.11	0.27
region_2	Regional dummy (Urban municipality =1)	0.15	0.15	0.00	1.00
region_4	Regional dummy (Urban SMA=1)	0.03	0.02	0.80	0.43

Table 8: Average bias and test statistics, PSM analysis, AR program

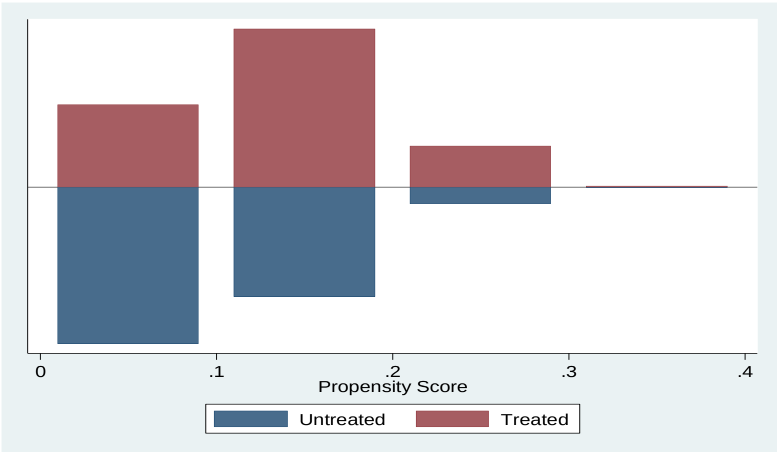
Sample	Pseudo R^2	LR chi^2	$p>chi^2$	Mean bias	Median bias	Std Dev bias
Raw	0.058	164.90	0.00	14.80	14.10	8.92
Matched	0.008	10.02	0.90	4.50	3.00	4.25

Sample size: 4286 households including 446 beneficiaries

Note: The bias is defined as the difference of the mean values of the treatment group and the (not matched/matched) control group, divided by the square root of the average sample variance in the treatment group and the not matched control group. For a given covariate *X*, the standardized difference before matching is the difference of the sample means in the full treated and control subsamples as a percentage of the square root of the average of the sample variances in the full treated and control groups. The standardized difference after matching is the difference of the sample means in the matched treated (that is, falling within the common support) and matched control subsamples as a percentage of the square root of the average of the sample variances in the full treated and control groups.

This analysis is based on 4286 households of which 446 are beneficiaries of ARP. Propensity scores ranged from approximately zero to one with a mean of 0.104. The PS was estimated with 18 variables from the enlisted in Table 7 and the higher order terms (squares and cubic terms of age and education variables). Pseudo R^2 of the probit model was 0.058 before matching and that reduced to 0.008 after the matching (Table 8). Likelihood ratio test also shows the there is no variation among the matched households. The matching was done using NNM algorithm. We also examined whether common support assumption holds using graphical analysis and found in each class of the propensity score there is a certain number of untreated households. So there are overlaps of the PS of beneficiary and non-beneficiary households in the data. So, we can assume that common support is hold (Figure 1).

Figure 1: Common supports, PSM analysis, Agriculture Rehabilitation Program



Impact of ARP on the outcome variables are shown in Table 9. Various indicators were chosen in the areas of labor allocation, income generating activities, investment and shock coping strategies. All indicators produced insignificant average treatment effect on the treated (ATT) based on Nearest Neighbor Matching (NNM). The ATT was significant for several indicators. These are income generating activities (farm and non-farm), labor allocation (farm and non-farm self-employment), and investment (agricultural assets, inputs). Farm activities increased by 0.40 units per household due to intervention. At the same time non-farm activity declined by 0.73 units. One of the areas of reduction of labor unit is day laborer in non-farm sector. This indicates that farmers may save time by involving in higher paid farming than day laborer activities in non-farm sector. Day laborer is usually a low paid job (In the sample average wage per day 120 Tk.). Farmers are earning higher income from crop sector (Tk 28118 per annum per household) due to program but giving up income from non-farm sector. Overall, the analysis suggests that ARP is a promising means of safety net for the marginal and small farmers. This type of safety net for farming communities could contribute more to productive outcomes. However, their access to credit is reducing for the safety net and they might be depleting some assets during shock (results are not statistically significant for credit and asset sold due to shock variables).

Table 9: Impact of Agriculture Rehabilitation Program on productive outcomes, 2010

Outcome indicators	Beneficiary households (Treatment)	Non-beneficiary households (Control)	ATT	t value
Number of Farm activities	0.94	0.54	0.40	8.25
Number of Non-farm activities	1.16	1.89	-0.73	-6.03
Self employed in farm activities	1.46	0.54	0.92	14.62
Self employed in non-farm activities	0.34	0.58	-0.24	-4.03
Salary of non-farm activity (Tk)	16915.92	16536.76	379.15	0.11
Income from crop production (Tk)	62249.20	19133.58	43115.63	10.4
Income livestock production (Tk)	8213.77	3290.16	4923.61	5.17
Value of agricultural assets (Tk)	15969.10	8546.87	7422.24	2.04
Fertilizer cost (Tk)	4135.11	1120.85	3014.25	8.01
Total credit (Tk)	8911.43	13281.61	-4370.18	-0.94
Land purchased	0.06	0.02	0.04	2.58
Non-food expenditure (Tk)	50467.80	50711.82	-244.01	-0.08
Expenditure on durable goods (Tk)	6279.18	5115.56	1163.62	0.89
Food expenditure (Tk)	510080.11	458240.38	51839.73	2.47
Education expenditure (Tk)	1149.12	889.50	259.61	1.86

4. Conclusions and Policy Recommendations

The productive outcomes of SSNP at the household include (i) changes in labour allocation/ employment, (ii) income generating activities, (iii) investments in land, tools, animals, family enterprises, durable goods and housing improvements, and (iv) changes in coping mechanisms. To assess the impact to the agriculture rehabilitation program as a social safety net program intervention we used PSM method.

The study found that ATT of agricultural rehabilitation program (ARP) produced significant effects on income generating activities (farm and non-farm), labor allocation (farm and non-farm self-employment), and investment (agricultural assets, inputs). So, it suggests that ARP is a promising means of safety net for the marginal and small farmers. Access to credit is found reducing for the safety net. The study can conclude, the result indicates in some extent selected agriculture rehabilitation program as a safety net programs is promising means for the vulnerable small farmer groups.

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