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Impacts of Bangladesh's Agricultural Rehabilitation Program as a Safety Net for Marginal and Smallholder Farmers

Ismat A. Begum[1], Mohammad. J. Alam[2], Shaheen Akter[3], Md. Mojammel Haque[4], Rezaul K. Talukder[5]

[1]Department of Agricultural Economics, Bangladesh Agricultural University, [2]Department of Agribusiness & Marketing, Bangladesh Agricultural University, [3]Department of Accounting and Finance, Open University, UK, [4]Graduate Training Institute, Bangladesh Agricultural University, [5]Poverty and Social Protection Advisor, Meeting the Undernutrition Challenge Program, FAO & Ministry of Food, GoB

This study empirically tests the impact of Bangladesh's agricultural rehabilitation program (ARP) on agricultural production at the household level. A propensity score matching approach is applied to 2010 Household Income and Expenditure Survey data. The sample comprised a control group of 4286 households against a treated group of 446 households. Various indicators such as labor allocation, income generating activities, investment and shock coping strategies were chosen to identify the impact on productive outcomes. The average treatment effect on the treated (ATE) was significant for income generating activities (farm and non-farm), labor allocation (farm and non-farm, self-employment) and investment (agricultural assets, inputs). Due to the ARP, labor moved from non-farm activities to farm activities, with farm activity increasing by 0.40 units, and non-farm activity declining by 0.73 units per household. These results suggest that the ARP is a promising means of providing a safety net for marginal and smallholder farmers in Bangladesh and can contribute to increased productive outcomes.

Keywords: Agricultural rehabilitation program, Propensity score matching, Productive safety net, Impact, Bangladesh

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Corresponding Author
Mohammad. J. Alam
Department of Agribusiness & Marketing,
Bangladesh Agricultural University
E-mail: alambau2003@yahoo.com,
mjahangir.alam@bau.edu.bd

INTRODUCTION

Agriculture is the largest sector of the Bangladesh economy, contributing about 15.16 percent to the GDP. About 40.6 percent of the total labor force is employed in agriculture (BBS, 2019). Over the last few years, Bangladesh has moved from being a major importer of food to becoming almost self-sufficient in the production of the staple rice and moved toward self-sufficiency in the production of other crops such as potato and maize, too. However, the country frequently suffers from disasters such as flash floods and tropical cyclones that affect yields drastically and disrupt the livelihoods of small and marginal farmers dependent on agriculture. Due to the high incidence of shocks, small and marginal farmers easily fall into poverty, seriously jeopardizing sustainable development.

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As in many other developing countries, social safety net programs (SSNPs) in Bangladesh play a vital role in reducing poverty through direct or indirect benefits to small and marginal farmers, especially in periods of natural calamities. The Household Income and Expenditure Survey 2010 collected information with respect to 30 public SSNPs in the country, of which10 were conditional, eight unconditional, five were credit schemes and three were conditional subsidy programs. Of these 30 SSNPs only the Agricultural Rehabilitation Program (ARP) was directly linked with agriculture.

The ARP is designed to rehabilitate smallholder and marginal farmers affected by flash floods or other natural calamities, providing assistance to support farmers to produce more food and to help reduce their deprivation. It provides marginal cardholding farmers with agricultural inputs through the Department of Agriculture Extension (DAE) in the Ministry of Agriculture. The inputs supplied include seeds, fertilizers and farm machinery (power tillers, threshers, batch driers, irrigation pumps etc.). Also, it seeks to build the capacity of farming households and community-based farmers' organizations. In the 2010-11 financial year, the ARP allocation was estimated to be 0.5 billion Taka, increasing to 1.2 billion Taka in 2018-19. In 2010, the number of ARP beneficiaries was 2.5 million farmers, increasing considerably since then (BER 2011, 2018).

In previous studies, the impacts of SSNPs on agricultural production have been found to be mixed. Gilligan and Hoddinott (2008) assessed the impact of Ethiopia's Productive Safety Net Program (PSNP), the largest social protection program in Sub-Saharan Africa outside of South Africa. The program had little impact on participants on average, due in part to transfer levels that fell far below program targets. Households with access to both the PSNP and packages of agricultural support were more likely to be food secure, to borrow for productive purposes, use improved agricultural technologies, and operate their own nonfarm business activities. Hoddinott (2008) found that safety net interventions contributed to agricultural and economic growth through their impact on asset creation, asset protection, resource allocation, and redistribution. Erin et al. (2010) explored whether cash transfer programs conditioned on human capital outcomes can influence agricultural production. The program was found to increase the value and variety of food consumed from own production and to increase land use, livestock ownership and crop spending. Their results support the hypothesis that transfers influence agricultural production and impacts are greater for households invested in agriculture. Maluccio (2010) examines the impact of a Nicaraguan conditional cash transfer program on measures of expenditures and productive investment. Despite clear evidence from a randomized evaluation that the program increased current expenditures, there is little evidence that it increased agricultural or non-agricultural investment. Fiszbein et al. (2011) described various experiences with conditional cash transfers to distil lessons about their effectiveness as crisis-response programs for households with children, to identify design features that can facilitate their ability to respond to transient poverty shocks, and to assess how they can complement other safety-net programs. Matin and Hulme (2003) argue that programs such as income generating Vulnerable Group Development (VGD), which has goals of livelihood protection and promotion should be a major focus for anti-poverty strategies because this program extended the reach of poverty reduction activities. They conclude that while such programs that mix livelihood protection and promotion should be a major focus for anti-poverty strategies, there will remain a role for more traditional social welfare schemes.

Several studies have investigated targeting, delivery mechanisms, operational performance, alternative design, impact assessment and so on of different social safety net programs (SSNPs) in Bangladesh (Ahmed, 2004; World Bank, 2006; Ahmed et al., 2007; Morshed, 2009; Khandaker et al. 2011). Notably, Khandker et al. (2011) examined the impacts of rural road projects using household-level panel data from Bangladesh and found that rural road investments reduced poverty significantly through higher agricultural production, higher wages, lower input and transportation costs, and higher output prices. However, with the exception of the present study[1],

[1]Earlier versions of this paper titled "Impact of Agricultural Rehabilitation Program in Bangladesh: A Propensity Score Matching Analysis" were presented at the pre-conference workshop of the 8th International Conference of Asian Society of Agricultural Economists, Dhaka, Bangladesh, 14-17 October, 2014 and the International Association of Agricultural Economists 2018 Conference, July 28-August 2, 2018, Vancouver, British Columbia.

there has not been an exploration of the impact of ARP on agricultural productivity.

Given the mixed findings on SSNPs and the dearth of information about the agricultural production-related outcomes of the ARP at the household level, and the strong implications of household productive activities on poverty in Bangladesh, it is important that an attempt is made to estimate the household level productive impact of the ARP. This will provide the policy makers at the ground level with information and recommendations that will help in framing effective SSNPs.

The remainder of this paper is organized as follows. The research methodology is presented next in section 2. The conceptual framework and procedure for selecting productive outcomes are presented in section 3. The results and discussion are presented in section 4. The last section presents the conclusions and policy recommendations.

METHODOLOGY

The hypothesis tested is whether the ARP facilitates significant changes in productive outcomes of beneficiary households compared to the non-beneficiary households. Specifically, the hypotheses tested are whether the agricultural rehabilitation program expedites significant changes in farm and non-farm labor allocation, income generating activities, productive asset accumulation and investments, shocks and coping mechanisms. The main research question is what are the productive outcomes of agricultural rehabilitation program at the household level? Further research questions are: (i) what are the impacts of ARP on labor allocation, (ii) can ARP beneficiaries use the SSN to support productive investment, (iii) how does the ARP fund affect beneficiaries' income generating activities, and (iv) what are the effects on risk coping strategies such as distress sales of productive assets.

The propensity score matching (PSM) approach is appropriate to analyze the impact of the Agricultural Rehabilitation Program (ARP) on productive outcomes. The advantage of the propensity score matching (PSM) model is that this approach does not necessarily require a baseline or panel survey (especially for the outcome variables). However, 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 (Rosenbaum and Rubin, 1983).

The impact is the difference between actual outcome and the outcome that would have happened without intervention. Counterfactual outcome is the unknown outcome, which would have happened without intervention. In the HIES 2010 data, we observe what has happened with ARP intervention, but we need to estimate what outcome would have happened without intervention.

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

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

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:

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

Where X is a vector of the covariates, and 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 support 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 can reduce the bias reasonably by avoiding potential misspecification when estimating the 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).

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 of the use of PSM is that it allows observational studies to be designed similar to randomized experiments. 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" among non-participants that have a propensity score very close to that 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 several other algorithms such as Caliper Matching, Radius Matching and Kernel Matching. The NNM selects households in the control group as matching partners for beneficiaries, based on 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 participation to the program.

Commonly, probit or logit models are applied to estimate PS. A probit model was applied 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).

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 the 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 HIES, 2010[2]. 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 based on the 2001 population census. The sample comprised 612 primary sampling units (PSUs) throughout the country, with 164 PSUs in urban areas, 392 PSUs in rural areas and 56

[2]The HIES 2010 was the latest dataset when we conducted this research. The latest round (final HIES 2016-17) of dataset was made available only in very recently, past but is still at the possession of Bangladesh Bureau of Statistics. Our research estimated the productive impacts of ARP and we believe that the direction of impacts would be similar to if the latest round had been used.

PSUs in small metropolitan areas (SMA). 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 were from rural areas and 4,400 from urban areas. HIES 2010 includes data on age, sex, marital status, religion/ethnicity, education, housing, income and expenditure, consumption, employment, health, basic services (water, sanitation and electricity etc.), assets description and social safety nets. The SSNP module was first introduced in HIES 2005 in which only 11 programs were included but its scope was 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 would not be an appropriate choice. HIES 2005 and 2010 are not a true panel. 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 the PSM approach.

The study has identified the households receiving benefits from the ARP only because our interest is to measure this program's impacts. To prevent overlapping with other programs, only households whose sole safety net benefit was the ARP are considered.

Only 6.3 percent of the population (i.e., 3508 out of 55580) was included in SSN programs, and thus considered here as SSN participants. The remaining 93.7 percent (52073) are considered as SSN non-participants (Table 1).

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.

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

SSNPs	Number of beneficiaries	Percent
Agriculture rehabilitation	560	16.0
Other SSNPs	2948	84.0
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
Did not know about the program	2045	4.40
Not fit for that program	29925	64.45
Fit for the program but not apply	1853	3.99
Due to shortness of budget	1769	3.81
Selection was not proper	9975	21.48
No program in this area	861	1.85
Total	46428	100.0

Source: Authors' calculation based on HIES, 2010.

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Out of 3508 beneficiaries, the ARP beneficiaries comprise only 560, which is 16 percent of total SSNPs beneficiaries (Table 2). Out of these 560 ARP participants, 114 participants benefited from at least one of the other 29 SSNPs. This left 446 sole ARP beneficiaries for the treatment group.

From the pool of non-participants, we identified a population eligible for SSN benefits by analyzing related questions included in the survey. The non-participant respondents in HIES 2010 were asked for the reasons that they were not included in SSN programs. This study considered for inclusion in the control group those respondents who stated that (i) they did not know about the program or (ii) they were fit for the program but did not apply, or (iii) they were excluded due to insufficient budget, or (iv) they stated that the selection procedure was not proper, or (v) they stated that there was no SSNP in their area. The distribution of causes of not being included in major SSNPs is presented in Table 3. The total number of individuals who stated at least one of the above five reasons falls into the probable control group which is 4286 households (16503 individuals) (Table 3).

THEORETICAL FRAMEWORK AND PROCEDURE FOR SELECTING PRODUCTIVE OUTCOMES

The provision of cash or in-kind support through safety net programs help smooth consumption and enable vulnerable people to bear greater risk and increase production at the household level. The concept of social safety net programs leading to productive impacts is built around the hypothesis that the provision of cash/in-kind transfers to vulnerable households has the potential to generate productive outcomes at the household level by investment in productive activities, asset accumulation, and change in labor allocation and ultimately to strengthen the local economy through multiplier effects on local goods and labor markets via economic linkages.

Safety net transfers often represent a significant share of household income and can be expected to help vul-

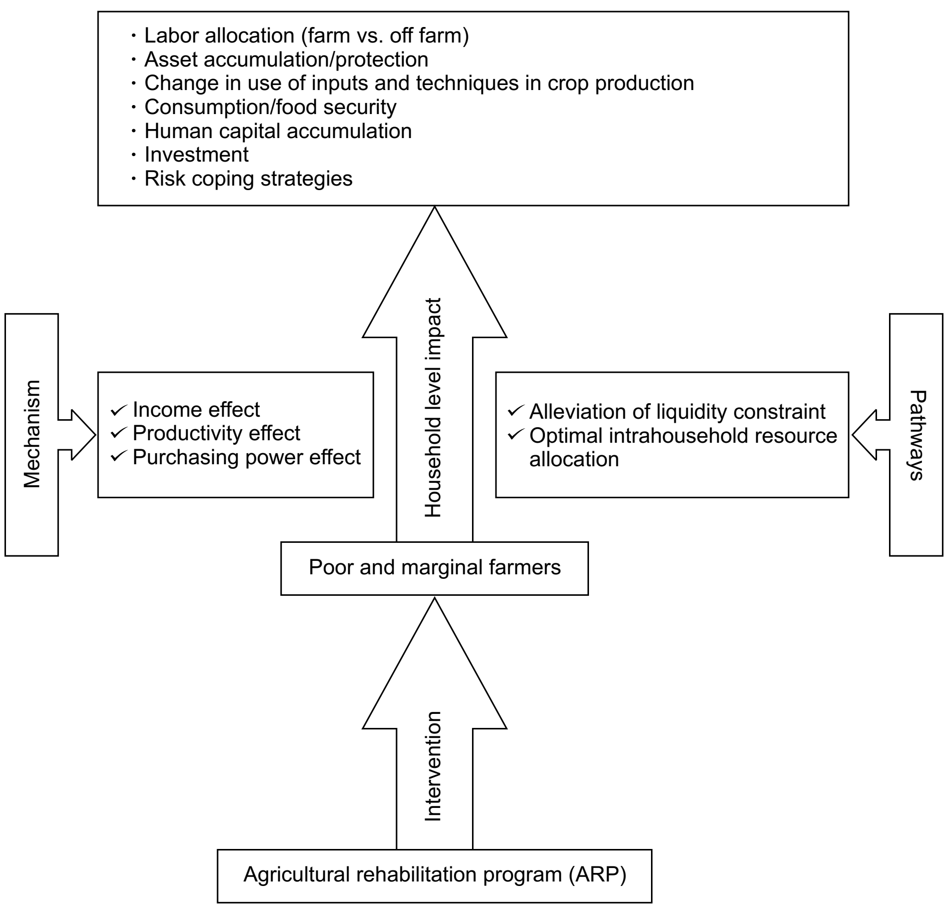

Fig. 1. Conceptual framework (Source: Partially adapted from Davis, 2012).

Table 4. Measurable productive outcome indicators at household level

Outcomes	Indicators	Measurable indicators	Imputed from 2010 HIES
Labor allocation	Relative farm employment	1) Average working hours per day per worker in farm activities	Calculating daily male and female hours in farm activities
	Relative non-farm employment	2) 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 number of self-employed activities involved	3) Number of self-employed in farm activities	Calculate total number of self-employed farm activities for each active members of the household add them to obtain the total for each household
		4) Number of self-employed in non-farm activities	Calculate total number of self-employed non-farm activities for each active members of the household add them to obtain the total for each household
	Total farm income	5) Per household from crop production	Calculating total income from crop production
		6) Per household from livestock production	Calculating total income from livestock
	Total non-farm income	7) Per household	Calculating total non-farm income (small business, cottage)
Investments	Land purchased	8) Dummy variable: if land purchased = 1	
	Fertilizer expenditure per household	9) Real expenditure on fertilizer, per household	Calculate household expenditure on fertilizer, & convert into real terms
	Real expenditure on durable goods & housing improvement	10) Real expenditure on durable goods & housing improvements per person	Calculate household expenditure on tools, animals, family enterprises, durable goods & housing improvements per person, convert into real terms
	Value of agricultural assets	11) Total value of agricultural assets per household	Total value of agricultural assets per individual
	Expenditure on education	12) Real expenditure on education	Calculate expenditure on education per person, convert into real terms
Shock and coping mechanism	Asset sold	13) Dummy variable: if assets sold due to shock = 1	
	Per capita consumption	14) Sum of per capita value of food expenditures 15) Sum of per capita value of non-food expenditures	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.
	Total credit	16) Dummy variable: if loan received from formal/informal sources = 1	

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nerable households overcome the bottlenecks that block their access to credit or cash and spur significant changes in household behavior. The study aims to find out how safety net transfers might impact on the productive outcomes of vulnerable households. In Figure 1, we provide some likely pathways linking the social safety nets and productive outcomes. One can see how these pathways can be used as a guiding framework for the empirical parts of this study, especially the productive outcomes of selected safety net programs.

Conceivably, safety net programs can affect productive outcomes via the following channels:

- Human capital formation: By facilitating the accumulation and improvement of human capital, transfers may enhance productivity and increases employability in the long term.
- Income generation: By weakening credit, savings and/or liquidity constraints, SSNPs can facilitate changes in income generating activities. This may include changes in labor allocation (to and/or from labor off farm and on farm); investment in productive activities (use of inputs); and accumulation of productive assets (such as farm tools, land or livestock, durable goods, housing improvement).
- Risk management: Regular and predictable provision of a safety net (cash or in-kind) may improve the ability to manage risk and shocks. This includes the avoidance of detrimental risk coping strategies (distress sales of productive assets, child school dropouts etc.); the avoidance of risk averse production strategies (safety or eat first); increased risk taking into more profitable crops and/or activities.

From the above discussion, several potential outcome variables emerge. The productive outcomes of ARP at the household level chosen for analysis are: (i) changes in labor allocation/employment; (ii) income generating

Table 5. Observable characteristics included as dependent & independent variables

Variables	Description	Mean	Standard deviation
Dependent variable			
Dummy	Dummy variables (Treated = 1)	0.16	0.47
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	Number of children 5-14 years	1.12	1.08
Male65	Number of male 65+ year old	0.12	0.33
Female62	Number 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

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 4. We considered a broad set of outcomes. Thematically, these are divided into four categories, detailed below.

Labor allocation: There is debate regarding whether the provision of a SSNP safety net reduces work effort. Hence, we focus on selecting specific indicators to assess labor allocation. One of the evaluation questions in this respect is whether SSNP intervention increases labor 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 surrounding 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 interventions increase or bring about changes in the value of farm assets, new land purchases, agricultural expenditure, durable goods and housing improvement. The study used household expenditure on tools, animals, family enterprises, expenditure on tools, animals, family enterprises, durable goods and housing improvements per person, converted into real terms.

Shock and coping indicators: Shock and coping indicators include 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 is 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, 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 6. Indicators of covariate balancing by variable

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 (number 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 number (from age 5 to 14)	1.03	0.99	0.63	0.53
female62	Female number (age 62 and above)	0.13	0.13	0.29	0.77
male65	Male number (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

RESULTS AND DISCUSSION

This section analyses the household income and expenditure survey (HIES) 2010 data to investigate the impact of ARP on productive outcomes at the household level. The primary inclusion criterion for ARP was that farmers must have operated land and farmers belong to the small and marginal farm category (0.05-2.49 acre). As detailed above, we chose 4286 households to include in the probit model as a probable control group from the households other than the treated group of 446 households.

Variables in PS estimation

The variables included in PS estimation are provided in Table 5. 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 SSNP. So, the study selected the variables age, gender, education of household head, characteristics of the house (number of people per rooms), own land etc., which were considered in selecting participants in the ARP as a government safety net program. Two thirds of the 22 exogenous variables listed in Table 5 had higher standard deviation than the mean showing wide variations.

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

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 5 (22 covariates) plus higher orders of age and education variables and so in total we included 24 covariates. Then the study excluded the variables which had statistically the same mean values between treated and control groups before matching. The criteria for variable selection were thus likelihood ratio test, Pseudo R^2, mean and median bias. Pseudo R^2 indicates how well X covariates explain the participation probability. We used PSmatch2 in STATA to do the analysis.

Probit scores were estimated using 17 characteristics variables from the list in Table 6. 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 have not shown the probit results because the model for the propensity score 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.

The balancing properties of characteristic variables are shown in Table 7. This shows that the control households are matched closely with the beneficiary households by the method of nearest neighbor matching. Propensity scores ranged from approximately 0.003 to 0.33 with a mean of 0.104. The PS was estimated with 17

Table 7. Average bias and test statistics

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.

variables from the enlisted variables in Table 6 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 7). The likelihood ratio test also showed that there was no variation among the matched households. The matching was done using the NNM algorithm.

Using graphical analysis, we also examined whether the common support assumption holds, and found in each class of the propensity score that there was 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 did hold (Figure 2).

The study used the Variance Inflation Factor (VIF) to gauge whether there is a problem of multicollinearity among the explanatory variables. When the VIF value is greater than 10, it indicates a multicollinearity problem. The VIF values of the explanatory variables included in the model were found to be well below 10, indicating

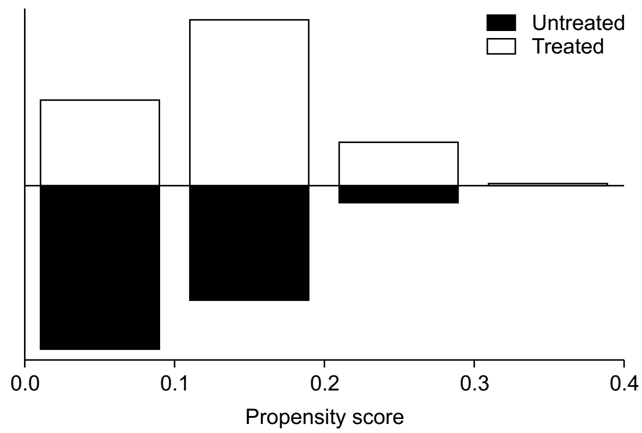

Fig. 2. Histogram of estimated propensity score between treated and untreated (control).

Table 8. Impact of Agriculture Rehabilitation Program on productive outcomes

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
Income from 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
Assets sold	0.06	0.04	0.02	1.37
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

that there are no multicollinearity problems among the explanatory variables.

The impact of ARP on the outcome variables are shown in Table 8. Various indicators were chosen in the areas of labor allocation, income generating activities, investment and shock coping strategies. The ATT was significant for several indicators. These are labor allocation (farm and non-farm self-employment), income generating activities (farm and non-farm), 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 was day laborer in non-farm sector. This indicates that farmers may save time by involvement in higher paid farming than day laborer activities in the non-farm sector. Self-employment in farm activities increased by 0.92 units per household due to ARP. At the same time, self-employment in non-farm activities decreased by 0.24 units per household. Day laborer is usually a low paid job (in the sample the average wage per day was 120 Tk[3]). Farmers are earning higher income from crops (Tk 43115 per annum per household) due to the program but giving up income from the non-farm sector. Income from crop production and livestock production increased by 43115 and 4923.61 units, respectively. Land purchased also increased but only by a small amount (0.04) and food expenditure increased by 51839.73 units. However, their access to credit reduced due to safety nets and they might be depleting some assets during shock (results are not statistically significant for credit and asset sold due to shock variables).

CONCLUSIONS AND POLICY RECOMMENDATIONS

The study found that participation in the 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). Overall, the analysis suggests that ARP is a promising means of providing a safety net for marginal and small farmers. This type of safety net for farming communities could contribute more to productive outcomes. Access to credit was found to be reduced by access to the safety net. Overall, the results indicate that agricultural rehabilitation as a safety net program is a promising means for the vulnerable small farmer groups and we conclude that ARP is more linked to productive outcomes. Different interventions might produce different outcomes and SSN system as being composed of a set of different interventions is thus capable to generate different productive outcomes. This implies that policymakers should think of implementing ARP and interventions like ARP to achieve different productive outcomes.

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DISCLAIMER

The findings and presentation of material in this paper are attributable to the authors and do not necessarily reflect the views of FAO, nor do they imply the expression of any opinion whatsoever on the part of FAO or of the Government of Bangladesh.

[3]Local currency (1 US$ = 85 Taka).

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