# Improving State Capacity to Target Extreme Poverty: An Evaluation of a Randomized Intervention in Bangladesh*

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**Abstract**

Scarce resources for social assistance intended to benefit the poor are often misallocated in developing countries. While national governments design social transfer programs with various eligibility criteria and formal application procedures, local governments in charge of selecting beneficiaries may have insufficient capacity and/or will to target government assistance benefits as envisioned. Existing research mostly refers to corruption as the main problem and neglects the potential relevance of capacity constraints. Given the scarcity of existing research on whether and how capacity constraints can be alleviated to improve targeting of social transfers, we evaluate a state-capacity-building intervention for the national Old Age Allowance program in Bangladesh in a clustered randomized controlled trial. Developed in collaboration with the Ministry of Social Welfare, the intervention includes training of local-government representatives on the national-government guidelines for the selection of beneficiaries and the provision of data on the target group. Our results show that the intervention did not improve the targeting performance even though the intervention components jointly and the training alone improved the knowledge of eligibility criteria among the local government representatives and the people in the target group pointing towards the relevance of both local will to implement the policy as nationally planned and capacity.

**Keywords:** social policy, targeting, local governance, randomized controlled trial, Bangladesh

**JEL Codes:** D91, I38, H55, H75

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# 1 Introduction

Local-government representatives and officials in the Global South work under severe constraints, not just with respect to financial and physical resources, but also with respect to access to relevant information and tools to process this information. These constraints are particularly severe in the poorest countries, where the effectiveness of public policies is crucial for the well-being of a large part of the population which suffers from extreme poverty (UNCDF and UNDP, 2012; UNDP, 2016; World Bank, 2004, 2017).

Social transfers, for example, may not reach the intended beneficiaries if local decision-makers lack resources and information. Typically, nationally designed social policies are implemented by local-government representatives and officials. There are two main reasons for discrepancies in the way policies are nationally designed and locally implemented (Lipsky, 1980; Niehaus et al., 2013; Pressman and Wildavsky, 1984; Steiner, 2000). First, local-government representatives have discretionary power with respect to how they implement certain rules and guidelines, and they have preferences which might not be well aligned with those of the national government. Second, their performance depends on the conditions under which they are working; they face certain capacity constraints in terms of training, information, financial resources, and time.

Despite the documentation of capacity constraints in the literature, research on interventions that aim to address poor implementation of public programs has not given much attention to whether and how these capacity constraints could be alleviated. It focuses primarily on measures improving accountability of public officials to reduce corrupt practices or on supporting citizens to claim their entitlements. These include performance-linked employment and salary schemes (Banerjee and Duflo, 2006; Bourdon et al., 2006, 2010; Duflo et al., 2012; Muralidharan and Sundararaman, 2011), increased information to the intended target group (Francken et al., 2009; Reinikka and Svensson, 2004, 2011), or other monitoring and reward systems to incentivize the responsible public officials (Banerjee et al., 2011; Deininger and Mpuga, 2005).

In their meta review on the effect of transparency on governance, Kosack and Fung (2014) emphasize that in many cases the problem is not that local officials or other service providers do not want to collaborate but a variety of other reasons, such as capacity constraints, affect their performance. In such situations, approaches focusing on monitoring and accountability may be even ineffective. The impact of building the relevant state capacity at the level of the local government remains to be examined. Further, while monitoring might be a cost-effective method for a single program (Muralidharan et al., 2018), the administrative and financial burden created by such efforts could become cumbersome and expensive when hundreds of policies need to be monitored in a country. Also for this reason, it is worthwhile to explore other channels, such as capacity building, to improve implementation of public programs.

It is hard to see how targeting for these programs can be effectively improved without relaxing the state-capacity constraints. Without reliable data on the poverty of the local population, how will a local-government representative or official correctly select those individuals who need the financial support the most? Similarly, even with the best of intentions, without appropriate training on eligibility rules and implementation guidelines, how will a local-government representative or official carry out a selection of most eligible beneficiaries according to the national guidelines? Both problems, the lack of income data and not knowing the government guidelines appear to be particularly severe in developing countries where resources for training are very constrained and most people work in the informal economy. These issues may even become worse if instead of local-government officials elected local-government representatives are in charge who act voluntarily as representatives. In Bangladesh, while the officials typically have university education, are competitively selected for their work as civil servants and trained for their specific tasks, the elected local representatives have very heterogeneous educational and professional backgrounds and lack formal preparation or training for the numerous responsibilities that they need to fulfill for a small honorarium.

Combining insights from existing literature with our own research on the local implementation of the national Old Age Allowance (OAA) program in Bangladesh, we aim to contribute to filling this knowledge gap by first examining the underlying reasons for mistargeting of a national social pension program for the elderly poor and second analyzing whether and how an intervention that relaxes capacity constraints can improve the targeting of social transfers. To answer this question, we evaluate an intervention that provides training as well as data on the target group to the Old Age Allowance beneficiary selection committee members. We further test for potential spill-over effects to the Widow Allowance scheme which uses similar poverty-focused targeting rules and selection procedures.

The results from our pre-registered analysis show that the intervention did not improve the targeting performance even though the intervention improved the knowledge of eligibility criteria among the local government representatives. Further, exploratorily we also shows that the beneficiaries' awareness of targeting rules improved due to the intervention. We further document in our exploratory analysis, the relevance of bribe payments in the context of beneficiary selection suggesting that both capacity constraints and corrupt practices need to be addressed at the same time shedding light on avenues for future policy-making and research.

The remainder is structured as follows. In Section 2, we provide background information on the Old Age Allowance in Bangladesh. We describe the selection criteria and processes as well as the the prevailing shortcomings of the current implementation. In section 3, we describe the intervention. In section 4, we elaborate our study design and the data. Section 5 presents the results and section 6 discusses the implications.

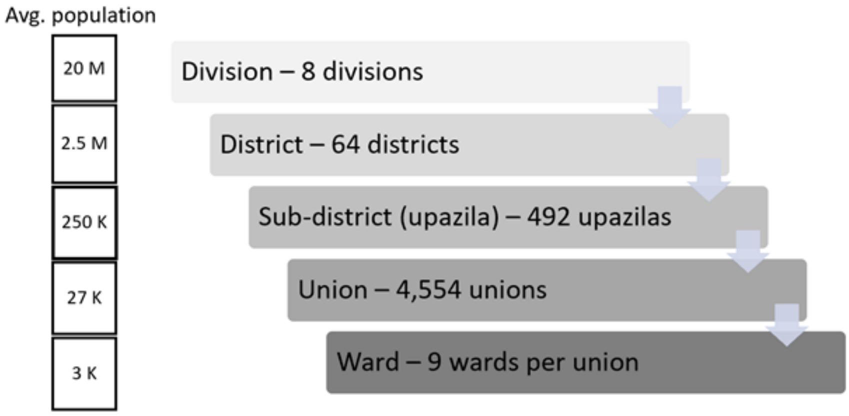
# 2 Background

## 2.1 Implementation guidelines

Since its introduction in 1998, the national government of Bangladesh provides the Old Age Allowance, a benefit of 500 Bangladeshi Taka (BDT; around 6 USD) per month, to selected beneficiaries. The primary objective of the scheme is to mitigate Old Age poverty. The national government provides the selection rules: Age, income, economic condition, physical condition and social condition. At the lowest level of the local government, also called Union Parishad (UP), an Old Age Allowance selection committee is in charge of selecting beneficiaries. This committee includes representatives of the municipality, called union, as well as representatives of sets of two or three villages, also called wards. Each union consists of nine wards and each ward is represented by one representative, called UP Member. As administrative level above the union, the subdistrict, called upazila, is also represented in the union selection committee. The 18 member selection committee includes the UP Chairman, nine UP Members, the Union Social Worker, three women representatives, called UP Women Members, each of them representing three wards, the Representative of the Upazila Chairman, the Representative of the Upazila Nirbahi Officer (i.e. of the chief executive officer of an upazila) and one female and one male Representative of the Local Member of Parliament at the union level (Government of Bangladesh, 2013). Figure 1 provides an overview of Bangladesh's administrative structure.

In terms of implementation, the national government describes the process as follows: Based on the annual budget allocation for the social pension, the national government first informs the local governments (OAA selection committee) at the union level about the number of additional pensions that will be available locally, and requests them to select new beneficiaries. Second, the selection committee informs the local population about the selection process by announcing the timing of the selection and the eligibility criteria. Third, the selection committee selects beneficiaries among the applicants and

Figure 1: Administrative structure Bangladesh




submits the list of selected beneficiaries to the Old Age Allowance selection committee at the upazila level. The upazila committee has the responsibility to review the list, make changes if required and approve it (Government of Bangladesh, 2013).

## 2.2 In practice

In practice, the selection of beneficiaries does not seem to follow these guidelines. In our qualitative and quantitative field research, we observed two frequently used practices. First, individual selection committee members inform citizens about the availability of new pensions, arrange their documents and include them on the list. Second, typically organized and monitored by the upazila level, so-called "open-field selections" are organized in which all the elderly from a union gather in front of the Union Parishad office on one day and the representatives go through the lines of men and women to make a selection following few of the above described selection criteria. While in the former case, knowing someone from the selection committee appears to be crucial, in the latter case the focus appears to shift towards the age as binding condition, local representatives ask about available family support and directly observe the physical condition of the elderly person. Other criteria such as household income or land ownership appear to be neglected in this ad-hoc selection.[1]

A pilot survey of beneficiaries and non-beneficiaries in eight unions in the same region as the randomized controlled trial documents that beneficiaries are as eligible as non-beneficiaries. Comparing the two groups in general in terms of their wealth (Figure 2) and more specifically in terms of their eligibility for the Old Age Allowance (Figure 3)

[1]Respondents in qualitative interviews and focus group discussions reported both scenarios. Further, one local Co-PIs attended open field selections to confirm these insights from qualitative interviews and focus group discussions.

shows that the two groups of beneficiaries (in green) and non-beneficiaries (in red) are statistically non-distinguishable.

Figure 2: Wealth of beneficiaries and non-beneficiaries

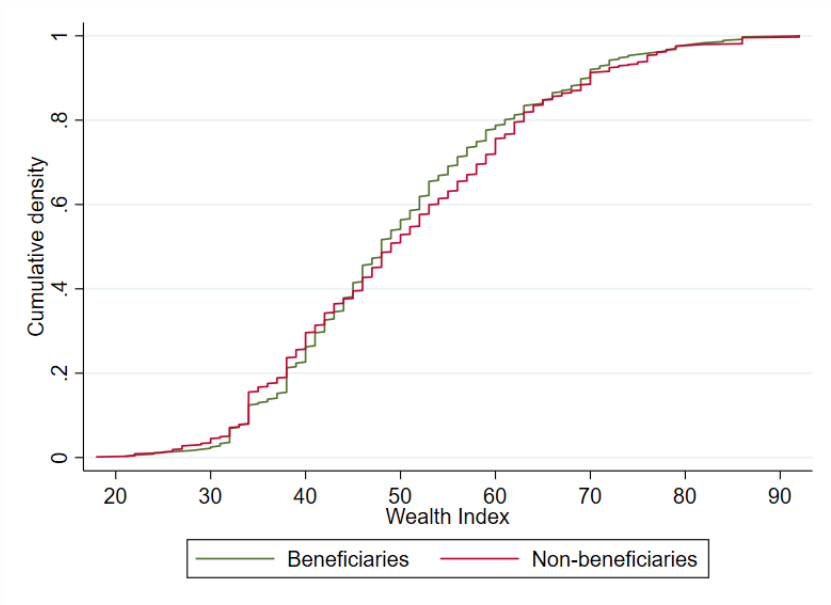
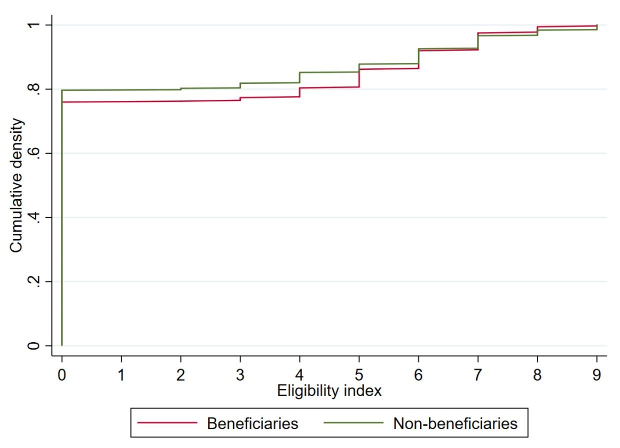


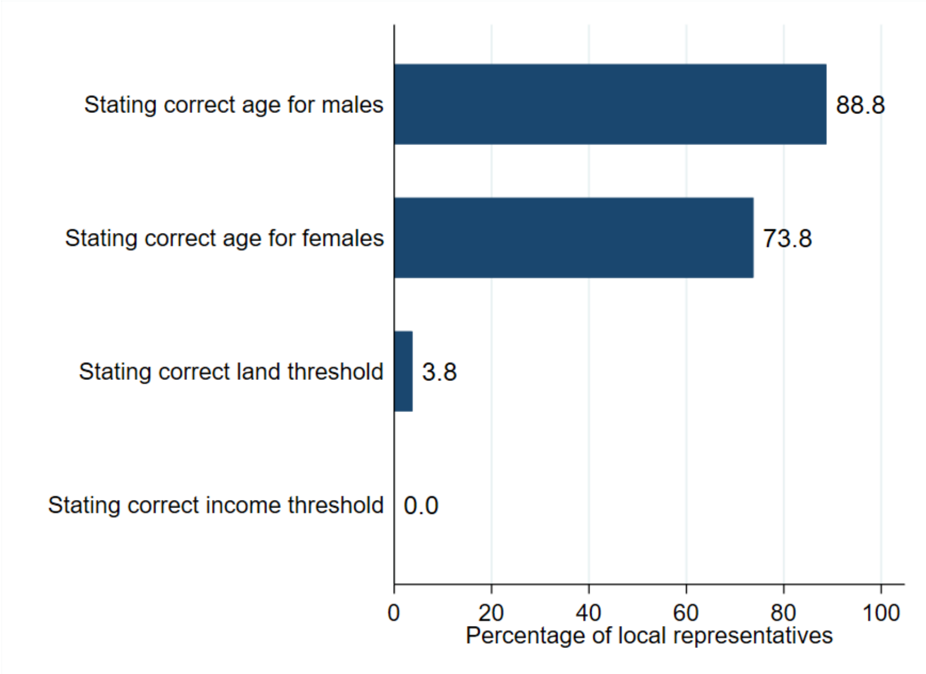

Figure 3: Eligibility of beneficiaries and non-beneficiaries




## 2.3 Underlying reasons

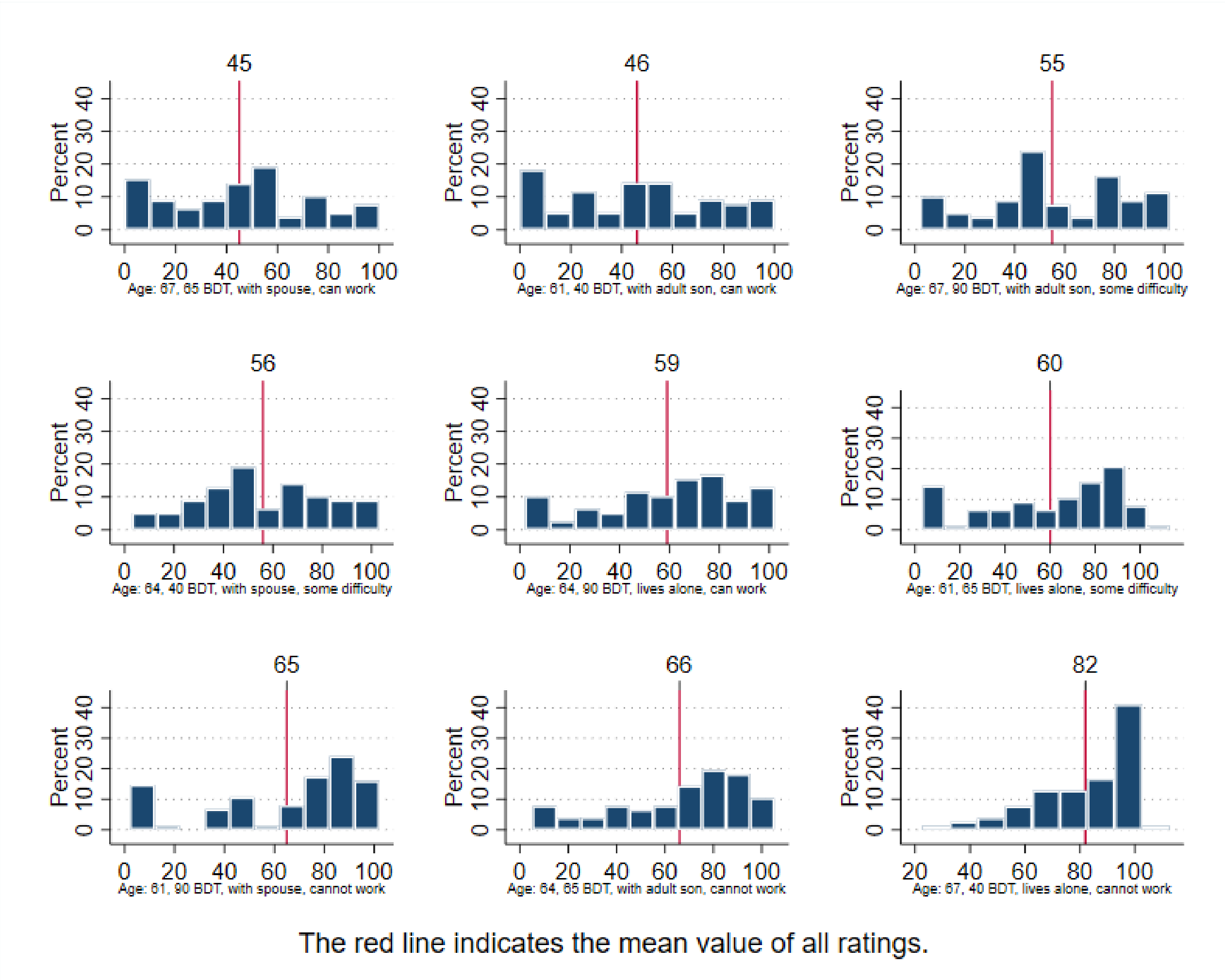
Various reasons may explain why the Old Age Allowance program is not targeted towards the poor. On the one hand, selectors in charge may struggle to follow the guidelines in practice. Our pilot survey of local government representatives demonstrates that those who are in charge of selecting beneficiaries have only very partial knowledge of the eligibility criteria (Figure 4). While most of the selectors know the correct age threshold for males (88.8%) and the correct age threshold for females (74.8%), only very few know the threshold for land ownership (3.8%) and for income (0.0%).

Figure 4: Selectors' knowledge of eligibility criteria




Also, selectors seem to struggle with assessing the eligibility of individuals (Figure 5). Being confronted with 18 fictional profiles (9 male and 9 female), the selectors gave eligibility ratings ranging from 0 to 100 for 16 out of 18 profiles and who assessed the eligibility explained 20 percent of the variation in the eligibility rating while the attributes explain only 12-14 percent according to the adjusted R-squared.

Figure 5: Eligibility ratings - female profiles



When being asked whether they need support for the eligibility assessment (Figure 6), 60% of the respondents reported that they very much need support and being asked for the type of support (Figure 7), 46% indicated that they need support in terms of staff and 37% indicated that they needed support in terms of data. While the former may be seen as a standard response (requesting more resources is generally very common), it is interesting that this is not reflected in a similar request for more funding. Furthermore, the strong request for more data cannot be explained by similar motives and seems to reflect a genuine need. It reflects the understanding that data (in the form of information about the applicants) is important for a proper selection.[2]

Figure 6: Support needed for eligibility assessment

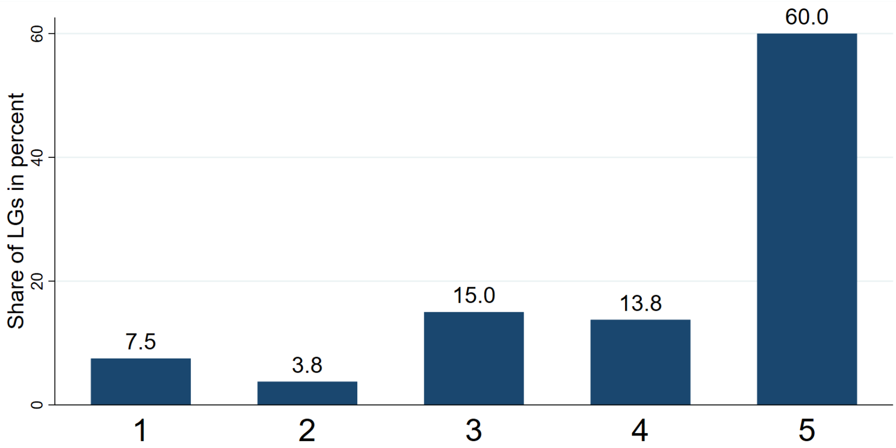
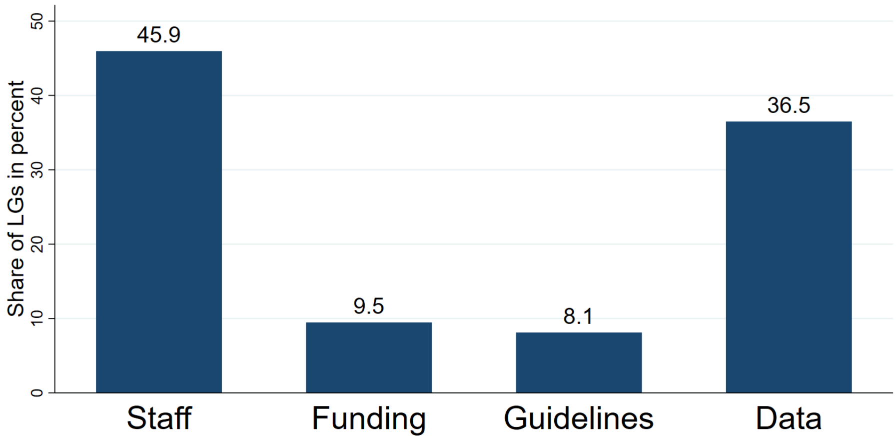



Figure 7: Type of support needed for eligibility assessment

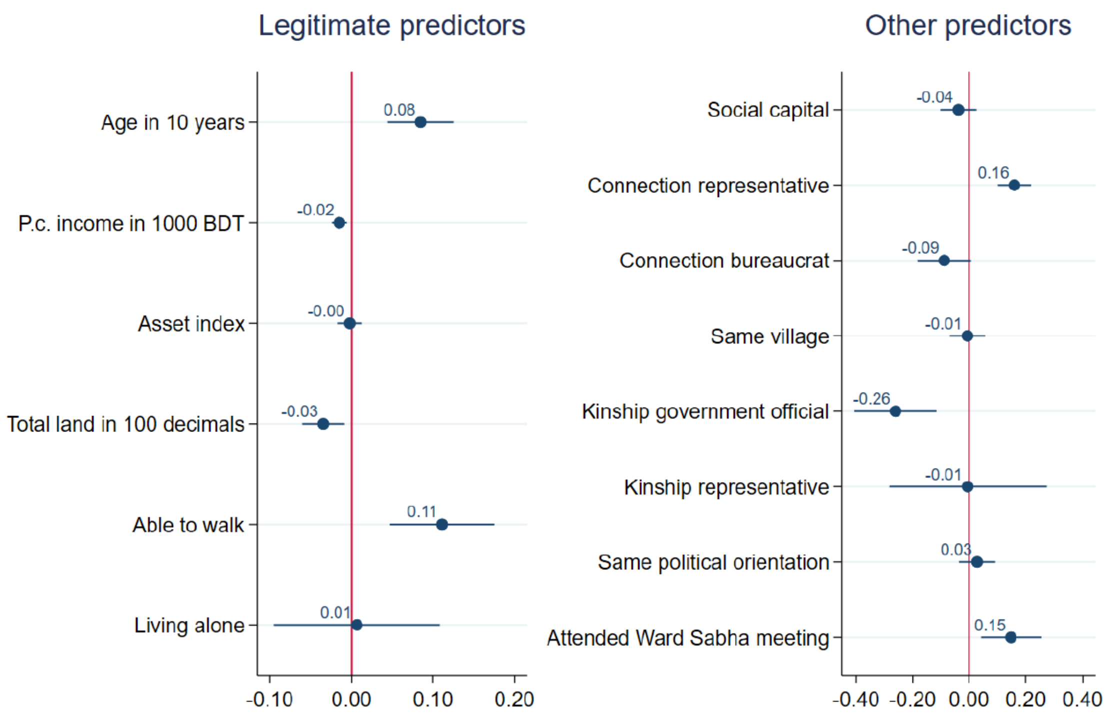



Finally, we observe that individuals who know the selectors personally have a much higher chance of getting selected (Figure 8). At first sight, this appears to be closely linked to corruption and selectors violating the guidelines for private gains. However,

[2]The corresponding survey question described data as information on the people in the target group.

given the need for support above, it could also signal that selectors simply rely on the local information that they have and they know better about people that they know than those that they do not know.

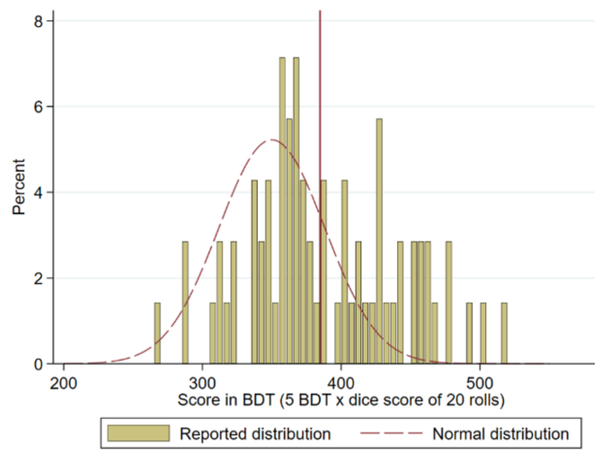
Figure 8: Legitimate predictors and other predictors of beneficiary selection




We focus in the field experiment on the capacity constraints, for the following reasons. First, an empirical analysis of whether more dishonest selectors are more likely to rely on personal connection, could not be confirmed in the pilot data (Figure 9). We use the dice game to illicit the preference for dishonesty using a well-established dice game by Fischbacher and Föllmi-Heusi (2013) in which subjects report in private the observed number on a die and thereby face an incentive to lie. Second, and more importantly, the literature on whether and how reducing capacity constraints can improve the targeting of social transfers is very scarce or almost non-existent. We therefore focus in this study on addressing the prevailing capacity constraints with an intervention in two components but integrate in our data collection an approach for better understanding the extent of corruption in the final selection.[3]

[3]Combining in this field experiment an intervention addressing corruption and an intervention addressing capacity constraints was not feasible due to budget constraints.

Figure 9: Dishonesty and the relevance of personal connections




| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Connection member | 0.132*** | 0.141*** | 0.182*** | 0.178*** |
| | (0.029) | (0.029) | (0.052) | (0.054) |
| Connection X dice score | -0.005 | -0.010 | | |
| | (0.028) | (0.029) | | |
| Dice score standardized | 0.011 | 0.024 | | |
| | (0.020) | (0.022) | | |
| Connection X dishonest | | | -0.074 | -0.055 |
| | | | (0.063) | (0.065) |
| Dishonest | | | 0.008 | -0.019 |
| | | | (0.044) | (0.048) |
| Avg. prediction of Y | 0.344 | 0.344 | 0.344 | 0.344 |
| Adj. R-squared | 0.058 | 0.061 | 0.060 | 0.062 |
| F-stat | 5.303 | 4.185 | 5.502 | 4.293 |
| P-value of F-stat | 0.000 | 0.000 | 0.000 | 0.000 |
| Union fixed effects | No | Yes | No | Yes |
| Observations | 1029 | 1029 | 1029 | 1029 |

# 3 Description of intervention

Our intervention design builds directly on these insights on the mistargeting of the Old Age Allowance in Bangladesh as presented in the previous section with a primary focus on addressing the prevailing capacity constraints. The underlying theory of change is that an intervention that improves the knowledge of eligibility criteria and provides information on the target group to those who are in charge of selecting beneficiaries, can improve the selection of beneficiaries. Given this theory of change, we designed an intervention with two components. We provide training to local government representatives and data on the target group to facilitate a more systematic and eligibility focused allocation of the social pension benefits. The intervention was carried out by an not-for-profit organization on behalf of the Department of Social Services.

The intervention was implemented at the union level. In each treatment union, the training component was provided to all selection committee members who are responsible for the selection of beneficiaries from all nine wards, but the target-group data collection and transfer was implemented only in three out of nine wards in each treatment union.

### Component 1: Training Old Age Allowance selection committee members on the beneficiary selection criteria

The training on the selection criteria for the OAA and on an information tool that we call the "Eligibility Information Card" (EIC) was developed in collaboration with the Ministry of Social Welfare. We designed one-to-one training sessions in which the trainer would show videos to the trainee and have a structured discussion of the content. The one-to-one approach allowed the trainer to engage more effectively with local representatives of different educational backgrounds including non-literate individuals and university graduates. The videos ensured that the same information reaches every trainee without being altered or interpreted differently by each trainer.

The trainers followed a training protocol consisting of showing videos, having structured verbal interactions with the trainee, conducting a short practice session, and ending with a quiz. The practice session included sorting hypothetical profiles following the national guidelines. In case someone missed or misunderstood content, the trainer repeated the explanations and answered any remaining questions. Each training session took between 45 and 90 minutes. The animated videos specifically produced for this intervention inform about the policy objectives of the Old Age Allowance and illustrate how a systematic selection of beneficiaries can be carried out. Figure 10 shows screenshots from the videos following the plot. At the end of the training, the trainer handed out a foldable poster to the trainee that summarized the three steps for beneficiary selection (Figure 11).

Similar to the development of the training program for local representatives, we also designed and carried out the training of trainers together with representatives from the National Academy of Social Services and the Department of Social Services. The training of trainers focused on the protocol and content for giving the training to the local-government representatives and familiarized the trainers with the required background knowledge on the scheme and the eligibility criteria.

### Implementation of both components

Due to their nature, the two intervention components were implemented by two different groups of field staff. First trainers, typically graduates of Social Science Master programs with the ability to explain the eligibility rules clearly and to communicate effectively with local representatives. Second, field officers, experienced enumerators who patiently and politely dealt with elderly people and knew how to interact with local representatives.[4]

The trainers worked in the municipalities before the field officers did. They typically fixed training appointments with local representatives a few days before reaching the union and carried out the training either at a local government office or at the local representative's home. Trainers further completed preparatory arrangements for the filling of EICs. They met the Upazila Social Service Officer, informed the UP Chairman and Members of the three selected wards, selected the venue where the EICs could be filled for the elderly,

[4]Due to security concerns and the requirement of frequent and extensive travel, all trainers and field officers were male.

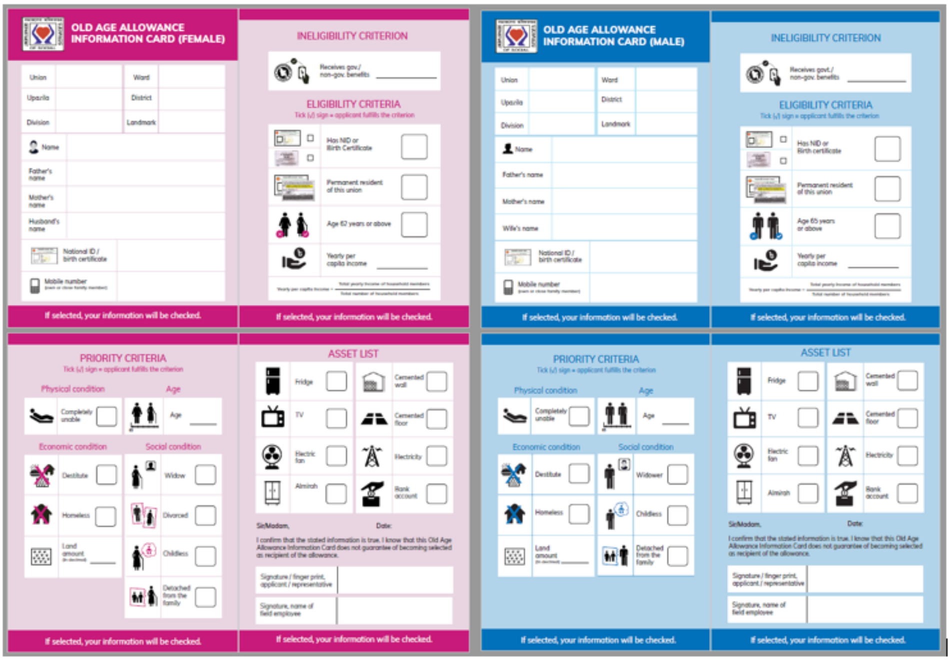
Figure 10: Training videos

Figure 11: Handover


**Component 2: Providing data on the Old Age Allowance target-group using Eligibility Information Cards**

We designed the EIC as shown in Figure 12 in collaboration with the Department of Social Services, under the Ministry of Social Welfare. Following the government manual, the EIC can be used to collect all relevant information on the elderly person in an easily accessible format. This includes identifying information (page 1), receipt of other benefits, fulfillment of eligibility criteria including age, permanent residency, and income (page 2), and fulfillment of priority criteria including physical ability to work, age and economic and social living conditions (page 3). On the last page, the field officer enters complementary economic information on the household including information on durable assets, having a bank account and electricity. To make the information easily understandable for people with very different educational backgrounds we used pictograms for each criterion and each criterion is marked with a tick or a cross except for income and land amount.

Figure 12: Eligibility Information Card for Females and Males




Both, field officer and elderly person signed the EIC.[5] The field officers filled two cards with the identical information. The first card was provided directly to the union selection committee with consent from the elderly. The second card was given to the elderly person who could use it to provide all relevant information to the selection committee members to apply for OAA. The elderly person could use this card to remind the local selection committee member of all her relevant information (in case the local selection committee member is not given attention to the provided EICs). After filling the EICs in the three different wards, the teams of field officers, made copies of the EICs for the project records and submitted the filled EICs to the Union Secretary. Most answers to questions asked during EIC filling, are easily observable locally (e.g. land ownership, physical ability to work, homelessness or social living situation). Nevertheless, to discourage misreporting for the few questions that cannot be easily observed (e.g. income), it was announced and clearly stated on the EIC that provided information will be checked if the elderly person is selected as OAA beneficiary (see Figure 4). Since rules with respect to age and social condition differ for females and males; and local representatives are requested to select a certain number of new beneficiaries among female elderly and male elderly separately every year, we designed two EICs — one for female potential beneficiaries and one for male potential beneficiaries that differ in the age and social condition (as well as, for practical reasons, in their color) as shown in Figure 12.

[5]If the elderly person could not sign, the person would put a thumbprint.

and organized the public announcements with a megaphone on a vehicle two days before, and again one day before the event. The venue had to be a public and central place easily reachable for everyone living in the ward. In the appendix, we provide all details on the step-by-step implementation of both intervention components (to be added).

# 4 Empirical methodology and data

For this study, we implemented a cluster-randomized controlled trial with one treatment group (with two sub-groups as explained below) and one control group from Fall 2019 until Spring 2021[6]. The randomized controlled trial was carried out in 80 unions located in 80 upazilas. The randomization into treatment and control group was stratified by district ensuring that in each district approximately the same number of unions was assigned either to treatment or control.

Given the two components of the intervention with the training given to all selection committee members and the data being provided for three wards, we compare in our analysis treatment areas that received training and data to control areas that did not receive either of the two and treatment areas where the representatives only received the training but no data to control areas that did not receive either of the two.[7]

This section first presents our research hypotheses and outcome measures. It then proceeds to describing the data sets and the regression models used for the estimation.

## 4.1 Hypotheses and outcome measures

Our primary hypotheses focus on the direct impact of the intervention on the targeting performance. With the secondary hypotheses, we examine the channel behind the impacts as well as the potential indirect impact of the intervention on another social transfer, the Widow Allowance. As primary outcome measure, we focus on the main objective of such social transfer programs, which is to reduce poverty. We use the Probability of Poverty Index (PPI) developed by Innovations for Poverty Action to compare the poverty status of newly selected beneficiaries in treatment unions with the poverty status of newly selected beneficiaries in control unions. The PPI is a general poverty measure that indicates how likely it is that a household is poor (Schreiner, 2013). The recently updated PPI for Bangladesh includes questions on location of residence, household size, household composition, highest grade completed by anyone in the household, ownership of durable

[6]We provide a timeline in the appendix.

[7]The alternative of having one treatment arm for the complete treatment and one treatment arm for the partial treatment was not feasible due to budget limitations.

assets, wall material, electricity connection and type of toilet used. The advantage is that it relies only on relatively few questions which are easily verifiable. For the impact evaluation, we use the PPI constructed for the subset of households including an elderly person i.e. a female at least 62 years old or a male at least 65 years old. Appendix C provides the list of survey questions used for the PPI and a more detailed description of the index.

Our main expectation is that the intervention providing practical support to local decision makers will improve the targeting of social pensions towards the elderly poor. Hence, we expect that newly selected beneficiaries in the treatment unions will be, on average, poorer than newly selected beneficiaries in control unions. Going beyond this general expectation, as described in the intervention section, our design also allows us to distinguish two types of impact assessments focused on the targeting of the social pension — the impact of the complete treatment vs. the impact of the partial treatment. To illustrate this, it is important to recall that in a treatment union, all 18 committee members responsible for selecting beneficiaries from all nine wards received the training but only three out of these nine wards received the data on the target group. The endline-data collection took place in six wards covering three wards where target-group data was provided, and three wards where target-group data was not provided to the selection committee. When comparing to the control group, this set up hence allows us to evaluate the impact of receiving the complete treatment, i.e. training and target-group data; and the impact of having received only the training. These two impacts are measured in comparison to unions in the control group where no intervention took place. The difference in the impact between the complete treatment and the partial treatment (if any) will indicate the impact of providing data, an important capacity constraint which has been neglected in previous research.

Focused on the Old Age Allowance, these are our primary hypotheses:[8]

Hypothesis 1: The joint provision of training and data on the target group increases the mean PPI / the mean eligibility index of newly selected Old Age Allowance beneficiaries in the treatment wards compared to newly selected beneficiaries in the control group (complete treatment).

Hypothesis 2: The provision of training increases the mean PPI / the mean eligibility

[8]In our pre-analysis plan, hypothesis 1 was split into two separate hypotheses with hypothesis 1 focused on the mean PPI and hypothesis 3 focused on the mean eligibility index. Similarly, hypothesis 2 was split into hypothesis 2 and hypothesis 4 with the former one focusing on the mean PPI and the latter one focusing on the mean eligibility index. Content-wise the pre-specified hypotheses were the same and they are only summarized here for readability.

index of newly selected Old Age Allowance beneficiaries in the treatment wards compared to newly selected beneficiaries in the control group (partial treatment)

If providing data on the elderly in the target group is relevant for the selection of beneficiaries, the effect size for the complete treatment should be larger than the effect size for the partial treatment. We will measure the difference in the impacts of complete and partial treatment and assess its statistical significance. While the PPI score is our main outcome of interest, we will also examine the impact on the eligibility index which is a weighted score indicating whether and to what extent newly selected beneficiaries fulfill the eligibility and priority criteria as stated in the implementation manual, also described in detail in Appendix C. As local representatives are trained to follow the selection criteria as per Old Age Allowance Manual, we expect to observe an improvement in the eligibility index.

Again, if the provision of data about the elderly in the target group is relevant, the effect size for the complete treatment should be larger than the effect size for the partial treatment. In terms of secondary research hypotheses, we plan to analyze first the expected channel behind the impact and second, the potential indirect impact on the beneficiary selection of the Widow Allowance. First, local representatives in treatment unions are expected to have a better knowledge of the selection criteria compared to local representatives in control unions.

Hypothesis 3: The intervention increases on average the knowledge of eligibility rules among the local representatives in the treatment group compared to the local representatives in the control group. We will test this hypothesis using a knowledge index which counts the number of correct answers to questions on eligibility criteria, priority criteria and selection procedures. explained in more detail in the appendix.

Second, as pointed out above, the intervention may have indirect impacts on the selection of beneficiaries for other social-welfare programs. We focus on the example of the Widow Allowance that follows similar rules and procedures and its selection of beneficiaries takes place at the same time. The group of people in the OAA selection-committee largely overlaps that of the Widow Allowance selection-committee and by having learnt a systematic way of selecting beneficiaries for the Old Age Allowance and having observed a systematic data collection approach, committee members might also be able to improve the selection of Widow Allowance beneficiaries.

Hypothesis 4: The intervention increases the mean PPI of newly selected Widow Allowance beneficiaries in the treatment group compared to newly selected Widow Allowance beneficiaries in the control group.

To examine the impact on the targeting performance of the OAA in Hypothesis 1-2 and 3 and 4, the units of analysis are the newly selected OAA beneficiaries. For Hypothesis 5, the units of analysis are the local representatives and for Hypothesis 6, the units of analysis are the newly selected Widow Allowance beneficiaries.

## 4.2 Data sets

### Baseline data

Our baseline data collection was conducted as a phone survey. The sample consists of all 18 selection committee members from all 83 unions in our study area. Assuming that every position is filled in all committees this would amount to in total 1494 selection committee members. Our team of enumerators managed to interview 92% of them (N=1378). The remaining 8% were either vacant positions, not reachable, postponed the call multiple times because they were busy or stated being unwilling to participate. The surveys lasted between 25 and 30 minutes. Baseline data-collection was focused on capturing whether and to what extent union selection committee members know the eligibility rules for the Old Age Allowance. Apart from these knowledge questions, we also collected data on their need for support for selecting beneficiaries and their willingness to lie for private gain using a dice game. In the dice game, the enumerator rolls a die 15 times and the respondent thinks for each die roll of a number between 1 and 6 and silently counts how many times the number on the die reported by the enumerator is matching with the number in her mind. For each match, the respondent receives BDT 20. With this dice game, we obtained a measure of (dis)honesty at the individual level for our exploratory analyses of potential heterogenous impacts. Described in more detail below, the impact of the intervention may depend on the willingness to apply the selection rules learnt in the training and to use the data from the EIC which might be linked to the measure of (dis)honesty. A very similar measure has been shown to predict corrupt behavior and support for rule-breaking by public sector employees in India (Hanna and Wang, 2014). So, it might be the case that it also relates to corrupt targeting practice. The baseline questionnaire further covered socio-economic variables such as education, literacy, land ownership and income, as well as working experience as local-government representative and party affiliation. In addition to the phone survey of local representatives, we use upazila statistics to check whether our samples are balanced. The balance checks presented in Table 1 and Table 2 use data from the baseline survey and administrative data from the upazila level. Our control and treatment samples are balanced in terms of the baseline data and in terms of the upazila level development indicators. Only reading ability is slightly higher among the representatives in the control group than in the treatment group (significant at the 5% level). We further present the p-value of the F-test for joint orthogonality of the covariates in predicting treatment status in the bottom row. The null hypothesis of joint orthogonality cannot be rejected.

Table 1: Balance check using baseline data survey of local representatives

| | Control | Treatment | (1) vs. (2), p-value |
|---|---|---|---|
| Female | 0.246 | 0.246 | 0.983 |
| Age | 45.334 | 45.870 | 0.330 |
| Years of education | 9.773 | 9.597 | 0.382 |
| Can read a sentence (self-reported) | 0.970 | 0.946 | 0.028 |
| Can write a sentence (self-reported) | 0.957 | 0.937 | 0.104 |
| Land ownership (decimals) | 291.925 | 260.831 | 0.181 |
| Monthly household income (in BDT) | 42300.289 | 48096.836 | 0.327 |
| First time representative | 0.721 | 0.737 | 0.511 |
| Years in current position | 4.750 | 5.059 | 0.214 |
| Knowledge index Old Age Allowance | 1.652 | 1.665 | 0.706 |
| Knowledge index Widow Allowance | 1.104 | 1.119 | 0.520 |
| Number of matches in dice game | 5.193 | 4.955 | 0.203 |
| N | 670 | 647 | |
| P-value of F-test of joint orthogonality | | | 0.1755 |

Table 2: Balance check using upazila level statistics

| | Control | Treatment | (1) vs. (2), p-value |
|---|---|---|---|
| Total population | 267535.906 | 263293.000 | 0.890 |
| Number of households | 65985.125 | 63239.500 | 0.701 |
| Rural population (%) | 85.827 | 88.181 | 0.333 |
| Poverty headcount ratio (%) | 29.191 | 29.509 | 0.890 |
| Extreme poverty headcount ratio (%) | 15.381 | 15.552 | 0.918 |
| Primary employment: Agriculture (%) | 69.061 | 70.221 | 0.701 |
| Primary employment: Industry (%) | 6.677 | 6.434 | 0.825 |
| Primary employment: Services (%) | 24.262 | 23.345 | 0.693 |
| Households with Electricity (%) | 44.073 | 42.544 | 0.642 |
| Households with flush toilet (%) | 24.318 | 24.781 | 0.860 |
| Literate population (18 years and older) (%) | 45.793 | 44.394 | 0.297 |
| Less than primary school completed (%) | 54.449 | 55.911 | 0.253 |
| School attendance among 6-10 years old (%) | 79.913 | 79.454 | 0.513 |
| Percentage of underweight children (%) | 33.506 | 33.931 | 0.414 |
| Households with tap water (%) | 2.699 | 2.787 | 0.927 |
| Population aged 65 and above (%) | 4.728 | 4.891 | 0.209 |
| N | 40 | 40 | |

**Endline data**

The endline-data collection focused on capturing whether the intervention improved the targeting of the benefits and/or the knowledge of eligibility and priority criteria. We collected data from newly selected OAA beneficiaries, from union selection committee members and from newly selected Widow Allowance beneficiaries. From the newly selected beneficiaries, we collected data on socio-economic variables (such as: education, land ownership, income), and variables required to calculate the Poverty Probability Index (PPI), the knowledge index of OAA/Widow Allowance selection criteria. Moreover, we collected data on personal connections to local representatives and officials now and two years ago. From the selection-committee members, we collected data on their knowledge of the OAA/Widow Allowance selection criteria as well as data on socio-economic variables such as education, literacy, land ownership and income along with working experience as local-government representative and party affiliation. We collected data from six wards in the treatment unions and three wards in the control unions. As mentioned earlier, we cover six wards in the treatment unions so that our endline-data consists of data from three wards where representatives were trained and received target-group data and from another three wards where representatives did not receive target-group data. In each ward, the sampling plan was to interview 5 randomly selected eneficiaries of OAA and 5 randomly selected beneficiaries of the Widow Allowance, both selected in the 2020 selection after our intervention phase. Since beneficiary lists had very different lengths across wards and unions, these targets could not always be fulfilled. While all beneficiaries were randomly ranked, the survey teams ended up interviewing fewer beneficiaries in some wards and more beneficiaries in other wards. Overall, the endline sample includes 1810 Old Age Allowance beneficiaries (compared to 1800 observations targeted), 1335 local government representatives (compared to 1440 targeted) and 1166 Widow Allowance beneficiaries (compared to 1200 targeted). The samples are split approximately equally between treatment and control.

## 4.3 Analysis

### 4.3.1 Main analysis as pre-specified

In the empirical analysis, we focus on measuring the impact on the PPI of newly selected OAA beneficiaries (H1 and H2), on the eligibility index (H3 and H4), on the knowledge index (H5), and on the PPI of newly selected Widow Allowance beneficiaries (H6). First on our primary outcome of interest, in each union, we measure the PPI for the surveyed newly selected beneficiaries, so that we have several measurement points. We estimate the below regression model to assess the intention-to-treat (ITT)[9] effect of the intervention:

$$Y_{ij} = \alpha + \beta T_j + \gamma X_j + \epsilon_{ij} \tag{1}$$

where $Y_{ij}$ is the measurement of the outcome variable PPI for beneficiary i in union j, $T_j$ is a binary indicator of treatment status of union j, $X_j$ is a vector of baseline characteristics of union j and $\epsilon_{ij}$ is the standard error clustered at the union level. As a robustness check, we also estimate the outcomes without baseline covariates.

As covariates in regression model (1), we include baseline values of local representatives' average knowledge index of OAA rules, their average honesty score, their reading ability, strata dummies (for each district) and relevant upazila level development statistics (namely total population, percentage of literate population, extreme poverty head count ratio and population 65 and above). These variables are chosen because they are expected to be good predictors of the outcome variable in the endline. We proceed analogously for testing the hypotheses on the eligibility index (H3 and H4) and the PPI of newly selected Widow Allowance beneficiaries (H6). When testing the hypothesis on the impact of the intervention on the knowledge index (H5), we adapt the regression model as follows:

$$Y_{ij} = \alpha + \beta T_j + \gamma X_{ij} + \epsilon_{ij} \tag{2}$$

where $Y_{ij}$ is the knowledge index of local representative i in union j, $T_j$ is again the binary indicator of treatment status of union j, $X_i$ is a vector of baseline variables of local representative i and $e_{ij}$ is the standard error clustered at the union level. We include as covariates individual-level baseline values of local representative's age, reading ability, years of education, knowledge index of OAA rules, and strata dummies (for each district). As a robustness check, we also estimate the regression model without baseline covariates. As mentioned above, we compare the impact estimate for full and partial treatment with each other from the regression models with PPI and eligibility index as outcome variables. This yields the estimated impact of providing data on the target group informing about the relevance of the data on the target group for the selection of beneficiaries. Since the lack of income data is a problem in many developing countries, this will provide important insights for future reforms in social policy implementation.

[9] As two unions in the treatment group had already completed their selection of new beneficiaries, we have a non-compliance rate of 5%.

### 4.3.2 Additional exploratory analysis

Besides the knowledge gaps being directly addressed by our intervention, we also examine the whether and to what extent the complete and partial intervention may improve the beneficiaries' knowledge of eligibility and priority criteria.

Going beyond the importance of considering the capacity constraints of the selectors in charge, we assess the prevalence of corruption and especially bribe payments in the context of beneficiary selection, we run a small list experiment in the endline data collection. Randomly chosen respondents were shown either five or six activities in a pictogram and asked how many activities they completed when they tried to get selected as beneficiary (following Gilens et al. (1998) and Blair and Imai (2012)).

The first list with five items (also called unveiled list) did not include the payment of a fee as an activity. The second list with six items (also called veiled list) included the payment of a fee as an activity. By comparing the reported average number of activities from the group that saw the veiled list with the group that saw the unveiled list, we can measure the percentage of individuals having paid a bribe in our sample.

# 5 Results

In the following, we will present our findings when testing the previously described hypotheses. We first examine the intervention's impact on targeting and then assess the impact on selector's knowledge of eligibility criteria as well as beneficiaries' knowledge of eligibility criteria. The results presented below were specified accordingly in our pre-analysis plan unless we mention explicitly that these are exploratory findings.

## 5.1 Impact on targeting

We examine the impact on the targeting performance according to our pre-specified hypotheses for the probability of poverty index and the eligibility index. For both indicators, our regression results show that the intervention — complete and partial — did not impact the targeting performance of the Old Age Allowance. In Table 3 and 4, we present the regression results first including covariates and then excluding covariates as pre-registered.

Table 3: Impact of complete treatment on eligibility

| | (1) Below national poverty line | (2) Below national poverty line | (3) Eligibility Index | (4) Eligibility Index |
|---|---|---|---|---|
| Training and EIC | 0.00931 | 0.00869 | 0.0930 | 0.101 |
| | (0.287) | (0.312) | (0.658) | (0.613) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 0.200 | 0.200 | 1.511 | 1.511 |
| N | 1214 | 1214 | 1214 | 1214 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of partial treatment on eligibility

| | (1) Below national poverty line | (2) Below national poverty line | (3) Eligibility Index | (4) Eligibility Index |
|---|---|---|---|---|
| Only training | -0.00229 | -0.00150 | 0.0621 | 0.167 |
| | (0.771) | (0.858) | (0.801) | (0.466) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 0.200 | 0.200 | 1.511 | 1.511 |
| N | 1207 | 1207 | 1207 | 1207 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## 5.2 Impact on selectors' knowledge of eligibility criteria

In the following, we examine whether and how the knowledge of eligibility criteria improved among the selectors. Overall, about one year after the intervention, in Table 5, we find that the intervention significantly improved the knowledge index by 0.211. Given the mean of the control group of 1.89, the average knowledge increased by 11 percent. The improvement in the knowledge index is primarily driven by an improved knowledge of the income threshold which increased by 15.1 percentage points for the selectors in the treatment group. The results in Table 6 are similar, when we regress the knowledge indicators on the treatment for all selectors surveyed in the endline and then control for baseline variables aggregated at the union level, upazila statistics and district fixed effects.

Table 5: Impact on selectors' knowledge of rules - matched respondents (EL and BL)

| | (1)<br>Know index | (2)<br>Income | (3)<br>Land | (4)<br>Female age | (5)<br>Male age |
|---|---|---|---|---|---|
| Treated | 0.227*** | 0.151*** | -0.000165 | 0.0444 | 0.0166 |
| | (0.000) | (0.000) | (0.993) | (0.185) | (0.124) |
| Control group mean | 2.82 | 0.16 | 0.04 | 0.75 | 0.94 |
| N | 1192 | 1192 | 1192 | 1192 | 1192 |

The sample includes all local government representatives that participated in baseline and endline. We control for individual-level baseline values of local representative's age, reading ability, years of education, knowledge index of OAA rules, and strata dummies (for each district). P-values are shown in parentheses. Standard errors are clustered at union level.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 6: Impact on selectors' knowledge of rules - all respondents (EL)

| | (1)<br>Know index | (2)<br>Income | (3)<br>Land | (4)<br>Female age | (5)<br>Male age |
|---|---|---|---|---|---|
| Treated | 0.262*** | 0.146*** | 0.00684 | 0.0592* | 0.0210* |
| | (0.000) | (0.000) | (0.724) | (0.073) | (0.096) |
| Control group mean | 2.82 | 0.16 | 0.04 | 0.74 | 0.94 |
| N | 1245 | 1245 | 1245 | 1245 | 1245 |

The sample includes all local government representatives that participated in the endline. Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at union level.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 5.3 Impact on targeting of Widow Allowance

We further examine targeting of the widow allowance with the general idea that learning how to assess the eligibility of applicants for the Old Age Allowance could also help selectors to assess the eligibility for the Widow Allowance. In Table 7, we cannot reject the corresponding null-hypothesis. Our results suggest that the intervention did not impact the targeting of the Widow Allowance.

Table 7: Widow allowance targeting impacts

| | (1) PPI | (2) Total land | (3) Ind. income | (4) Assets |
|---|---|---|---|---|
| Training and EIC | -0.00538 | -1.288 | -154.7 | -0.0274 |
| | (0.565) | (0.641) | (0.124) | (0.822) |
| Control group mean | 0.17 | 19.26 | 1427.50 | 2.63 |
| N | 1166 | 1166 | 1166 | 1166 |

We control for baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## 5.4 Impact on beneficiaries' knowledge of eligibility criteria

Finally, we examine in Table 8 exploratorily whether and how the intervention impacted the knowledge of eligibility criteria among the beneficiaries. Compared to the selectors, beneficiaries know much less about the eligibility criteria. On average in the control group, beneficiaries know only 0.56 eligibility rules. The intervention increases this by 0.386 or 68 percent. Through the intervention, beneficiaries learn primarily about the age cutoff for males and females. The impact is very similar in areas that received training and EIC and areas that only received training. Apparently, as shown in Table 9, beneficiaries learnt in treatment areas about the age cutoffs through various channels: When interacting with selectors that were trained or during EIC filling when interacting with our field staff as well as potentially present local government representatives, or simply noticing it by looking at the EIC.

Table 8: Beneficiaries: Knowledge index

| | (1) Complete | (2) Partial |
|---|---|---|
| Training and EIC | 0.386*** | |
| | (0.000) | |
| Only training | | 0.278*** |
| | | (0.000) |
| Control group mean | 0.56 | 0.56 |
| N | 1214 | 1207 |

Dependent variable is knowledge index of OAA criteria. We control for baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at union level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Beneficiaries: Knowledge of age cutoff

| | (1) Male age | (2) Male age | (3) Female age | (4) Female age |
|---|---|---|---|---|
| Training and EIC | 0.168*** | | 0.150*** | |
| | (0.000) | | (0.000) | |
| Only training | | 0.128*** | | 0.103*** |
| | | (0.001) | | (0.000) |
| Control group mean | 0.32 | 0.32 | 0.07 | 0.07 |
| N | 1214 | 1207 | 1214 | 1207 |

Dependent variable is knowledge of age cutoff. We control for baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at union level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### 5.5 Potential role of corruption

There are two potential reasons of why the targeting performance did not change. Either selectors do not change the quality of their selection because of the challenge of handling too many applications for a very small number of pensions and the difficulty to aggregate many rules to assess the overall eligibility. Or alternatively, selectors do not want to change how they select beneficiaries as their way of selecting allows them to obtain monetary benefits in the form of bribes.

As described above, we use a list experiment to measure the prevalence of bribe payments. Randomly chosen respondents were shown either five activities excl. fee payment or six activities including fee payment and were then asked to state the number of activities they completed when they tried to get selected as beneficiary. By comparing the reported average number of activities from the group that saw the veiled list with the group that saw the unveiled list, we can measure the percentage of individuals having paid a bribe in our sample. Table 10 shows that on average, about 19 percent of the Old Age Allowance beneficiaries and 17 percent of the Widow Allowance beneficiaries reported having paid a bribe to be selected as beneficiaries suggesting that corruption continues playing an important role for targeting of social pension beneficiaries.

Table 10: Payment of application fee

| | (1)<br>N Activities<br>OAA | (2)<br>N Activities<br>OAA | (3)<br>N Activities<br>WA | (4)<br>N Activities<br>WA |
|---|---|---|---|---|
| Veiled list | 0.192$^{***}$ | 0.183$^{***}$ | 0.166$^{***}$ | 0.156$^{***}$ |
| | (0.000) | (0.000) | (0.003) | (0.005) |
| N matches dice game | 0.0756$^{*}$ | | 0.0845 | |
| | (0.070) | | (0.107) | |
| Covariates | Yes | No | Yes | No |
| Control group mean | 3.54 | 3.54 | 3.51 | 3.51 |
| N | 1812 | 1812 | 1166 | 1166 |

Dependent variable is number of activities completed when applying for allowance. We control for baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at union level.

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# 6 Discussion

Our results overall demonstrate that the intervention — complete and partial — did not improve the targeting of social pensions. We document that even one year after the intervention, there is still an impact on the knowledge of the eligibility criteria. While selectors mainly learnt about the income cutoff, the beneficiaries gained knowlegde on the age cutoffs.

Training on eligibility rules and providing data on people in the target improved knowledge eligibility criteria but appears insufficient to reduce mistargeting of social transfers. Learning about the income cutoff may not have led to substantive changes in targeting because the income threshold is so low that practically nobody can leave with an per capita income below the cutoff. Hence, learning about the income cutoff, apparently, was not of much use for the selectors in charge.

Our study does not allow us to identify why the targeting performance did not improve. However, we document that even after having received our training and the data through the eligibility information cards, major capacity constraints remain and corruption appears to play a substantial role. Future research will need to address both at the same time — capacity constraints and corruption — to improve the targeting of social transfers.

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# A Timeline

| | |
|---|---|
| May 2018 | Pilot data collection |
| July 2018 - Dec 2019 | Development of intervention with Ministry of Social Welfare |
| Sept-Oct 2019 | Baseline data collection |
| Jan-Feb 2020 | Implementation of intervention with its two components |
| Mar-Jul 2020 | Selection of beneficiaries by local governments |
| Feb-Mar 2021 | Endline data collection |

# B Description of indices

## B.1 Probability of poverty index

As described in the main text, the PPI developed by Innovations for Poverty Action weighs responses to a small set of survey questions to compute a score, which then indicates the likelihood of a household living in poverty. A lower score indicates a higher likelihood of living in poverty. Different poverty lines can be applied including absolute and relative poverty lines as well as national and international poverty lines. “This PPI is based on data from Bangladesh’s 2016 Household Income and Expenditure Survey (HIES) 2016 produced by Bangladesh Bureau of Statistics and was released in July 2020. In order to construct this PPI, only households with at least one elder member were included. Elder is defined as men (women) who are 65 years (62 years) or older.” (Innovations for Poverty Action, 2020). The age cutoffs follow the age-based eligibility criteria for the Old Age Allowance in Bangladesh. The Elder PPI includes the following questions:

1. In which division does the household live?
2. How many household members are there in the household?
3. How many household members are between 0-9 years of age?
4. How many household members are between 10-17 years of age?
5. What was the highest grade completed by anyone in the household?
6. Does your household own a refrigerator?
7. Does your household own a fan?
8. What is the construction material of the walls of the main room?
9. Does the household have an electricity connection?
10. What kind of toilet facility do members of your household usually use?

## B.2 Eligibility index

According to the implementation manual 2013, there are ineligibility, eligibility and priority criteria to select beneficiaries for the Old Age Allowance (OAA). A person is ineligible for OAA if she receives any other government or non-government benefit regularly such as other social safety nets, government pension or formal sector pension. To be eligible for OAA, an individual needs to fulfill all four eligibility criteria:

1. Has to be a permanent resident.
2. Has to have National Identity Card or birth certificate
3. Has to be 62 years of age or more for females and 65 years or more for males.
4. Annual per capita income (i.e. annual household income divided by the number of household members) has to be less than BDT 10,000.

The eligibility index is 0 if the person either fulfills the ineligibility criterion or does not meet one of the required eligibility conditions. To select only few among the eligible elderly for OAA, the government prescribes the use of priority criteria. However, these criteria are hard to implement on the ground as government guidelines tend to lack clear instructions. Such as according to the economic condition, priority should be given in the order of destitute, homeless and landless, but there is no clear instruction on how to measure destitution. To simplify these different conditions for our analysis, four conditions are prioritized to create the eligibility index. These are age, ownership of land, living with adult child or alone, and physical ability to work.

**Age:** An elderly receives either 1, 2 or 3 based on the number of years an elderly is older than the cutoff. Below, we show the scoring method:

| For male elderly | |
|---|---|
| Rule | Score |
| 65 ≤ age ≤ 69 | 1 |
| 70 ≤ age ≤ 75 | 2 |
| age ≥ 76 | 3 |

| For female elderly | |
|---|---|
| Rule | Score |
| 62 ≤ age ≤ 66 | 1 |
| 67 ≤ age ≤ 72 | 2 |
| age ≥ 73 | 3 |

**Land ownership:** Elderly receive 1, 2 or 3 depending on how much agricultural land their household owns. Below, we show the rules for the scores.

| **Rule** | **Score** |
|---|---|
| Land ownership > 100 decimals | 1 |
| 50 decimals ≤ land ownership ≤ 100 decimals | 2 |
| Land ownership < 50 decimals | 3 |

According to the manual, if an elderly lives in a household that owns less than 50 decimals of land excluding the dwelling house, the elderly will be considered as landless.

**Social condition:** Depending on whom the elderly are living with, they receive a score ranging from 1 to 3 for the social condition:

| Rule | Score |
|---|---|
| Lives with adult son/daughter | 1 |
| Lives with other adult family member except son/daughter | 2 |
| Lives alone | 3 |

**Physical condition:** We use the ability to walk as a proxy for ability to work following the scoring rules below.

| Rule | Score |
|---|---|
| Able to walk without difficulty | 1 |
| Able to walk with some difficulty | 2 |
| Able to walk with severe difficulty or unable to walk | 3 |

## B.3 Knowledge index - Selection committee members

During endline-data collection, the selection committee members were asked questions on the eligibility and priority criteria for the Old Age Allowance. Based on correct/incorrect responses, we count the number of correct responses indicating the local representative's knowledge of eligibility and priority criteria. The following questions were used for the calculation of the knowledge index corresponding to a count of correctly stating the eligibility/priority rules:

1. Female age cutoff
2. Male age cutoff
3. Landless cutoff
4. Income cutoff
5. Eligible if receiving government pension?

## B.4 Knowledge index - Beneficiaries

During endline-data collection, the beneficiaries were asked questions on the eligibility and priority criteria for the Old Age Allowance. Based on correct/incorrect responses, we count the number of correct responses indicating the beneficiary's knowledge of eligibility and priority criteria. The following questions were used for the calculation of the knowledge index corresponding to a count of correctly stating the eligibility/priority rules:

1. Female age cutoff
2. Male age cutoff
3. Landless cutoff
4. Income cutoff

# C Summary statistics

Table A1: Summary statistics Old Age Allowance beneficiaries

| | mean | p50 | sd | min | max | count |
|---|---|---|---|---|---|---|
| Prob. poor elder national poverty line | 0.21 | 0.16 | 0.15 | 0.01 | 0.92 | 1812 |
| Eligibility index | 1.60 | 0.00 | 3.28 | 0.00 | 12.00 | 1812 |
| Ind. monthly income | 1760.56 | 625.00 | 2146.53 | 0.00 | 22542.00 | 1812 |
| Total land | 41.21 | 12.00 | 96.11 | 0.00 | 3034.50 | 1812 |
| Asset count | 3.23 | 3.00 | 1.66 | 0.00 | 8.00 | 1812 |
| Asset count quintile | 2.82 | 3.00 | 1.57 | 1.00 | 5.00 | 1812 |
| Asset quintile PCA | 2.89 | 3.00 | 1.59 | 1.00 | 5.00 | 1812 |
| Knowledge index | 0.77 | 1.00 | 0.85 | 0.00 | 3.00 | 1812 |
| Training and EIC | 0.50 | 0.00 | 0.50 | 0.00 | 1.00 | 1214 |
| Only training | 0.50 | 0.00 | 0.50 | 0.00 | 1.00 | 1207 |
| Female | 0.45 | 0.00 | 0.50 | 0.00 | 1.00 | 1812 |
| Age | 71.57 | 70.00 | 6.97 | 53.00 | 108.00 | 1812 |
| Rajshahi | 0.40 | 0.00 | 0.49 | 0.00 | 1.00 | 1812 |
| Rangpur | 0.60 | 1.00 | 0.49 | 0.00 | 1.00 | 1812 |

Table A2: Summary statistics Widow Allowance beneficiaries

| | mean | p50 | sd | min | max | count |
|---|---|---|---|---|---|---|
| Prob. poor national poverty line | 0.17 | 0.12 | 0.16 | 0.00 | 0.93 | 1166 |
| Ind. monthly income | 1372.28 | 875.00 | 1469.77 | 0.00 | 21458.00 | 1166 |
| Total land | 18.67 | 5.00 | 41.96 | 0.00 | 706.00 | 1166 |
| Asset count | 2.97 | 3.00 | 1.61 | 0.00 | 8.00 | 1166 |
| Asset count quintile | 2.60 | 3.00 | 1.56 | 1.00 | 5.00 | 1166 |
| Asset quintile PCA | 2.66 | 3.00 | 1.58 | 1.00 | 5.00 | 1166 |
| Only training | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 590 |
| Female | 0.99 | 1.00 | 0.08 | 0.00 | 1.00 | 1166 |
| Age | 52.90 | 53.00 | 8.95 | 21.00 | 83.00 | 1166 |
| Rajshahi | 0.40 | 0.00 | 0.49 | 0.00 | 1.00 | 1166 |
| Rangpur | 0.60 | 1.00 | 0.49 | 0.00 | 1.00 | 1166 |

Table A3: Summary statistics of aggregated union statistics

| | mean | p50 | sd | min | max | count |
|---|---|---|---|---|---|---|
| Mean (Can read) | 0.96 | 0.94 | 0.05 | 0.71 | 1.00 | 80 |
| Mean (Can write) | 0.95 | 0.94 | 0.06 | 0.71 | 1.00 | 80 |
| Aggregate knowledge index | 1.66 | 1.69 | 0.22 | 1.13 | 2.06 | 80 |
| Mean (No of matches) | 5.08 | 4.91 | 1.01 | 2.25 | 9.00 | 80 |
| Upazila total population in thousands | 267.61 | 231.57 | 135.42 | 90.76 | 706.60 | 80 |
| Upazila population 65 plus in thousands | 12.91 | 10.83 | 6.49 | 3.62 | 29.20 | 80 |
| Upazila percentage literate | 45.19 | 43.86 | 5.96 | 34.16 | 64.93 | 80 |
| Upazila HCR extreme poor | 15.51 | 14.61 | 7.28 | 3.97 | 32.42 | 80 |

# D Individual wealth indicators: Income, land and assets

Table A4: Impact of complete treatment on individual income and total land ownership winsorizing extreme values

| | (1)<br>Ind. Income | (2)<br>Ind. Income | (3)<br>Total land | (4)<br>Total land |
|---|---|---|---|---|
| Training and EIC | -189.5 | -160.9 | -7.370* | -6.763* |
| | (0.136) | (0.174) | (0.068) | (0.098) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 1660.3 | 1660.3 | 34.7 | 34.7 |
| N | 1214 | 1214 | 1214 | 1214 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Impact of partial treatment on individual income and total land ownership incl. extreme values

| | (1)<br>Ind. Income | (2)<br>Ind. Income | (3)<br>Total land | (4)<br>Total land |
|---|---|---|---|---|
| Only training | -107.2 | -91.40 | -6.936 | -5.597 |
| | (0.475) | (0.516) | (0.377) | (0.431) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 1660.3 | 1660.3 | 34.7 | 34.7 |
| N | 1207 | 1207 | 1207 | 1207 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Impact of partial treatment on individual income and total land ownership winsorizing extreme values

| | (1) Ind. Income | (2) Ind. Income | (3) Total land | (4) Total land |
|---|---|---|---|---|
| Only training | -78.57 | -47.30 | 1.127 | 0.685 |
| | (0.559) | (0.697) | (0.812) | (0.878) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 1660.3 | 1660.3 | 34.7 | 34.7 |
| N | 1207 | 1207 | 1207 | 1207 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Impact of complete treatment on asset ownership

| | (1) Assets count quintile | (2) Assets count quintile | (3) Assets PCA quintile | (4) Assets PCA quintile |
|---|---|---|---|---|
| Training and EIC | -0.172 | -0.171 | -0.120 | -0.137 |
| | (0.189) | (0.188) | (0.364) | (0.297) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 2.92 | 2.92 | 2.98 | 2.98 |
| N | 1214 | 1214 | 1214 | 1214 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Impact of partial treatment on asset ownership

| | (1) Assets count quintile | (2) Assets count quintile | (3) Assets PCA quintile | (4) Assets PCA quintile |
|---|---|---|---|---|
| Only training | -0.0241 | -0.0559 | 0.00637 | -0.0452 |
| | (0.839) | (0.645) | (0.958) | (0.709) |
| Covariates | Yes | No | Yes | No |
| Control group mean | 2.92 | 2.92 | 2.98 | 2.98 |
| N | 1207 | 1207 | 1207 | 1207 |

Covariates include baseline variables aggregated at the union level, upazila statistics and district fixed effects. P-values are shown in parentheses. Standard errors are clustered at the union level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$