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

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Abstract

Scarce resources intended to benefit the poor are often misallocated in the Global South. Existing research focuses on the effectiveness of anti-corruption measures and supporting citizens in claiming their entitlements but gives little attention to the capacity deficits of local governments. Focusing on supply-side constraints, we evaluate a state-capacity-building intervention for the national Old Age Allowance program in Bangladesh. 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, in particular, the provision of data on the target group. The design of our randomized controlled trial allows us to measure the impact of providing training as well as of providing training together with data on the targeting performance. We further assess the relevance of providing data for the selection. Finally, we examine the intervention's indirect impact on the targeting of another social transfer program. [150 words]

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

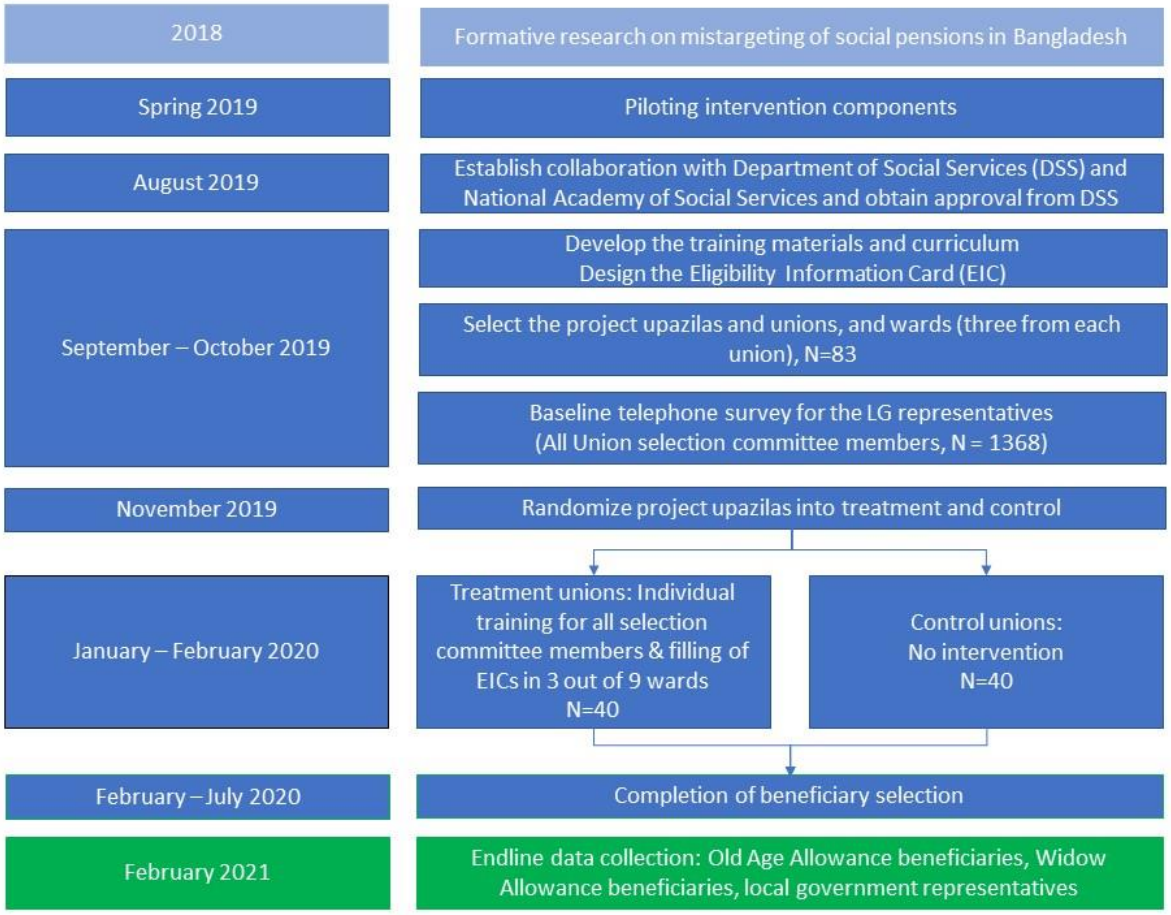
JEL codes: D91, I38, H55, H75

Study pre-registration: AEA RCT Registry, AEARCTR-0004510, https://www.socialscienceregistry.org/trials/4510

Timeline:

Based on the results from our formative research on mistargeting of social pensions carried out in 2018, we designed an intervention with two components. We subsequently piloted the intervention in Spring 2019 and obtained government approval for data collection and implementation of the intervention in August 2019. In October 2019, we completed the baseline data collection and carried out a final pilot of an improved version of both intervention components in November 2019. The implementation of both intervention components was completed in January-February 2020. Initially, the endline-data collection was scheduled for August-September 2020. However, due to the COVID19 pandemic, we now intend to collect our endline-data in February 2021. The expected time for completion of the study is June 2021. *Figure 1* summarizes the timeline of the project. The milestones in blue have already been completed, the remaining milestone of endline-data collection is shaded in green.

Figure 1: Timeline



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 & 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, Atanassova, Bertrand, & Mullainathan, 2013; Pressman & 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 perfectly 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, 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 & Duflo, 2006; Bourdon, Frölich, & Michaelowa, 2006, 2010; Duflo, Hanna, & Ryan, 2012; Muralidharan & Sundararaman, 2011), increased information to the intended target group (Francken, Minten, & Swinnen, 2009; Reinikka & Svensson, 2004, 2011), or other monitoring and reward systems to incentivize the responsible public officials (Banerjee, Kumar, Pande, & Su, 2011; Deininger & 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, Niehaus, Sukhtankar, & Weaver, 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.[1] 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. 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? Similarly, 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? While not knowing the government guidelines may be a relevant problem around the world, the lack of income data is particularly severe in developing countries where people need social benefits the most. These issues may even become worse if instead of local-government officials elected local-government representatives are in charge. 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 analyzing whether and how an intervention that relaxes these 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.

In Bangladesh, the Old Age Allowance, a targeted cash transfer from the government for elderly poor, is already one of the most important social-welfare schemes in the country in terms of the number of beneficiaries[2] (Bangladesh Bureau of Statistics, 2019) and it is expected to become even more important as demographic change progresses. This motivates our focus on this scheme. Our extensive formative field research with the same target population shows high rates of mistargeting of the OAA program. We find considerable leakage of about 40% and that overall

[1] For instance, currently there are 143 different social safety nets being implemented in Bangladesh.
[2] 4.9 million elderly in 2019-20 (Department of Social Services, 2020).

beneficiaries are not significantly more eligible than non-beneficiaries according to a number of measures, including a general poverty score (see *Figure A.1* in *Appendix A*). We further find that local-government representatives lack knowledge of the eligibility criteria as well as tools or practical assistance to target the benefits as they should according to the government guidelines. As a result, local-government representatives use their local knowledge to select beneficiaries (Asri et al., 2020). Drawing from these findings, we designed an impact evaluation that assesses a capacity-building intervention in close cooperation with the Ministry of Social Welfare of Bangladesh.

For the evaluation, we implement a cluster-randomized controlled trial with one treatment group (with two sub-groups as explained below) and one control group. The intervention consists of a training session for local-government representatives belonging to the OAA selection committee on selection rules and the provision of data on the target group for the assessment of the eligibility of potential beneficiaries. The focus lies on comparing municipalities that received both training and data to those that did not receive either of the two. However, our design also enables us to assess the impact of training without data provision. Importantly, the difference between these two impact measures then indicates the relevance of providing data on the people in the target group to the local selection committee. This distinction is in particular relevant for scaling up later on, as training only would be much easier (and cheaper) to provide than access to data on the target group.

The main outcome measure of interest will be the targeting performance measured by comparing the eligibility in terms of a general poverty measure of newly selected beneficiaries between treatment and control municipalities. A secondary outcome measure will be a weighted eligibility index following closely the government guidelines for eligibility and prioritization in the selection.

The intervention may also have indirect impacts on the targeting performance of other schemes. Those who select OAA beneficiaries are also often in charge of selecting beneficiaries for such other programs and the criteria related to poverty tend to be similar. Furthermore, our intervention may raise the awareness among local representatives that some standard requirements need to be met for beneficiary selection that include knowledge of government criteria and the broad collection of data on who meets these criteria within the community. In our study, we will assess potential side effects on the selection of Widow Allowance beneficiaries using a survey of newly selected beneficiaries of the Widow Allowance.

The endline surveys of newly selected OAA beneficiaries, newly selected Widow Allowance beneficiaries and local-government representatives are yet to be conducted while the baseline data collection and the implementation of the intervention were already completed in October 2019 and February 2020, respectively.[3]

In *Section 2*, we provide background information on the Old Age Allowance in Bangladesh and its prescribed selection criteria and processes. In *Section 3*, we present our research design including a description of the intervention, our hypotheses, the sample and power calculations. *Section 4* informs about the data and *Section 5* explains the empirical analysis. In *Section 6*, we illustrate how we plan to interpret potential results. In the appendix, we provide more detailed information on our formative research (*Appendix A*), the implementation of the intervention (Appendix B) and the construction of dependent variables (*Appendix C*).

2. Background

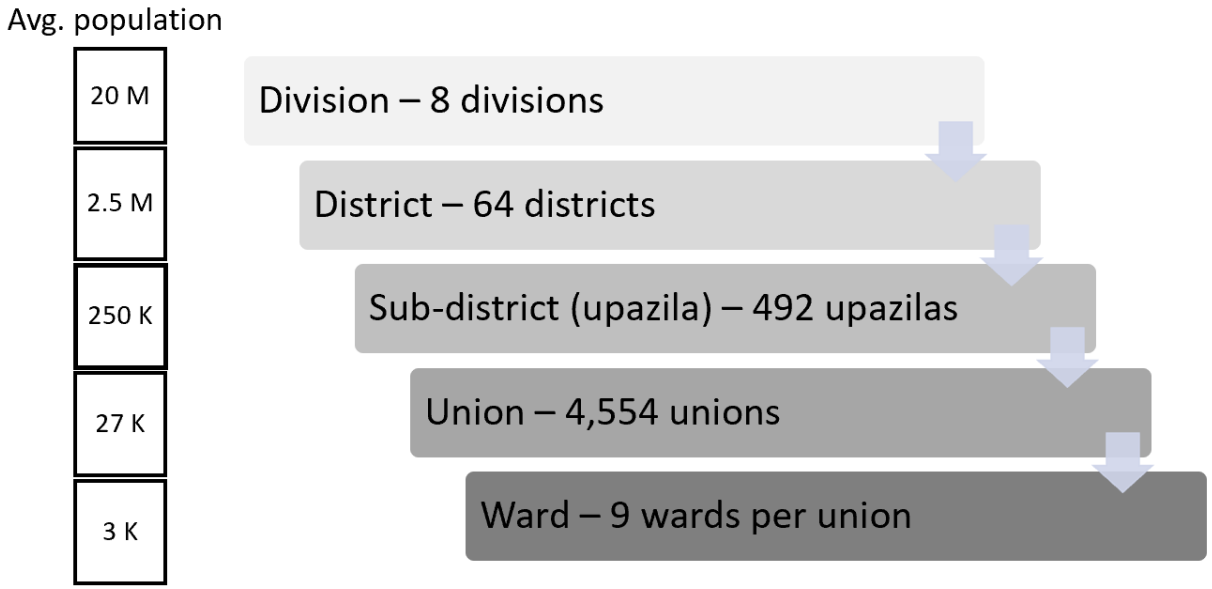
Since its introduction in 1998, the national government of Bangladesh provides the Old Age Allowance, a benefit of 500 Bangladeshi Taka (BDT; around 6 USD) per month, to selected beneficiaries. At the lowest level of the local government, also called Union Parishad (UP), an Old Age Allowance selection 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-level 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).[4] *Figure 2* 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

[3] To the best of our knowledge, this would be the first experimental study examining the impact of a state-capacity-building intervention on the targeting performance of a social-transfer program.
[4] For ease of reading, in the following, we use the terms selection committee members and local representatives interchangeably.

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 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).

Figure 2: Administrative structure of Bangladesh



Source: Authors' illustration.

The official eligibility criteria describe that women and men have to be at least 62 and 65 years old, respectively; applicants have to show a national identity card or a birth certificate as a proof of their age. The annual per capita income in the household of the elderly person has to be less than BDT 10,000 and the elderly person must not receive other benefits from the government. Since resources for the Old Age Allowance are limited, among the eligible applicants, priority should be given to homeless elderly, destitute elderly, elderly who live in a household that owns less than 50 decimals of land, elderly who do not live with a family and elderly who cannot work (Government of Bangladesh, 2013). The government manual does not describe how to measure the different criteria (such as destitute) or how to weigh the different criteria for prioritization.

Typically, the selection of beneficiaries by local governments does not follow the procedures described in the manual. Our recent study (Asri et al., 2020) provides qualitative as well as

quantitative evidence on how the selection of beneficiaries deviates from the guidelines. *Appendix A* provides further information on our formative research.

3. Research design

To examine whether and how relaxing existing capacity constraints can improve the selection of beneficiaries of the Old Age Allowance, we use a cluster-randomized controlled trial to evaluate the impact of the intervention. In the following, we first present the intervention, then explain our hypotheses and finally describe the sample and statistical power.

3.1 Intervention

Our intervention design builds directly on our formative research on mistargeting of the Old Age Allowance in Bangladesh (Asri et al., 2020) showing that the selection of beneficiaries hardly follows the eligibility criteria described by the national government. While some official selection criteria, such as age and income, do play a limited role in the selection of beneficiaries, we also find that other factors, such as personal connections and participation in public meetings, play a significant role. At the same time, most local agents in charge of the selection lack knowledge of the eligibility rules, and do not have access to data that could inform the selection of beneficiaries. Consequently, they often rely on their local knowledge and select people whom they know. We do not find evidence that such behavior of the local representatives can be empirically attributed to corruption.[5] Rather it appears to be the lack of data on the target group which drives the relevance of personal connections. Typically, those who are well connected to local representatives are not the poorest and most eligible beneficiaries (Asri et al., 2020).

The intervention implemented in January-February 2020 involved the training of the OAA selection committee at union level on OAA rules, and the provision of relevant data on the target group for the assessment of the eligibility of potential beneficiaries. As mentioned in Section 2, every union consists of nine wards. 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.

We explain each intervention component in more detail below.

[5] We proxy corruptibility by an honesty score, which is widely used in Experimental Economics (Fischbacher & Föllmi-Heusi, 2013). See Section 4 for more details.

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

To develop a training for all members of the union selection committee on the selection criteria for the OAA and an information tool that we call “Eligibility Information Card” (EIC, described below), we collaborated with the Department of Social Services and with the National Social Service Academy, under the Ministry of Social Welfare. Based on the insights from our formative research, we chose videos over verbal instruction to engage more effectively with local representatives of different educational backgrounds including non-literate individuals and university graduates. This also ensures that the same information reaches every trainee without being altered or interpreted differently by each trainer. We further chose one-on-one training over group training to prevent influence of unknown group dynamics and to ensure that our trainers could adjust the pace of the training instruction to each representative’s understanding and needs.

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 3* shows screenshots from the videos following the plot.[6]

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. Trainers arrived in the union always ahead of the teams of field officers as the training needed to be completed before target-group data collection and transfer would take place in a union.

[6] The videos are available upon request.

Figure 3: Video scenes

Source: Authors' illustration.

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

We designed the EIC 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.[7] 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.

Both, field officer and elderly person signed the EIC. 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 may 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 submitted the filled EICs to the Union Secretary.

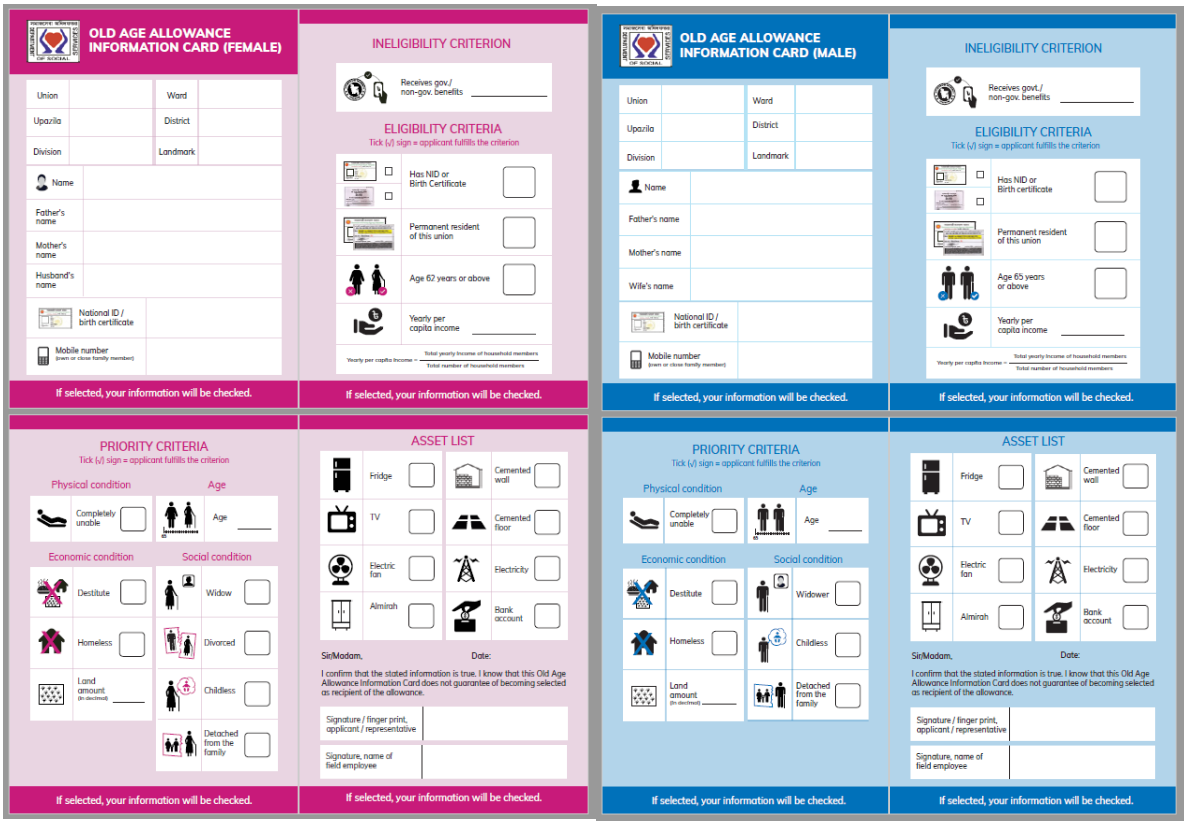
Most answers to questions asked during EIC filling, are easily observable locally (e.g. land ownership, physical ability to work, homelessness or social living situation). Nevertheless, to discourage misreporting for the few questions that cannot be easily observed (e.g. income), it was announced and 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

[7] The government manual does not suggest using this economic information on the household as eligibility criteria. However, as the prescribed criteria on income and land amounts are often noisily reported and hard to verify, we decided in collaboration with the ministry, to provide this as complementary information to the local representatives. The variables included here are commonly used in proxy means tests in developing countries and are strong predictors of household's wealth in Bangladesh (Chakraborty, Fry, Behl, & Longfield, 2016).

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 4*.

Figure 4: Eligibility Information Card for Females and Males



Note: We used the Bangla version of the EICs for the intervention. Source: Authors' illustration of selection rules described in the OAA Implementation Manual (Government of Bangladesh, 2013).

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 deal with elderly people and know how to interact with local representatives.[8]

[8] Due to security concerns and budget constraints, all trainers and field officers are male.

The trainers worked in the municipalities before the field officers did. They typically fixed 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, 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. *Appendix B* provides all details on the step-by-step implementation of both intervention components.

3.2 Hypotheses

Our primary hypotheses focus on the direct impact of the intervention. With the secondary hypotheses, we plan to 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 will focus on the main objective of such social transfer programs, which is to reduce poverty.[9] We will 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 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.

Obviously, both treatment and control group were hit by economic shocks during the Covid19 lockdown. On average, these shocks should have hit them equally. In any case, we will make sure that the PPI items relate to the time before the lockdown and the selection as well. It seems

[9] Alternatively, we could have focused on measuring to what extent individuals fulfill eligibility and priority criteria. However, as the government does not prescribe clearly how to weigh or aggregate the different eligibility and priority criteria, building an eligibility index remains arbitrary. In contrast to that, the poverty score is built on those variables that best predict consumption expenditures below the poverty lines for the chosen context and subset of households in the population including an elderly member.

highly likely though that most of these items will not have been affected by these shocks (see the list of questions in *Appendix C*). Moreover, we will add a section in the endline survey, in which we try to assess how helpful the Old Age Allowance benefits were during the lockdown in terms of consumption smoothing for example in terms of the share of household income during this difficult time period.

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 three types of impact assessments focused on the targeting of the social pension. 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 will take 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. Importantly, the difference in the impact between the complete treatment and the partial treatment 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:

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

If the 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 substantially 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.

Hypothesis 3: *The joint provision of training and data on the target group increases 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 4: *The provision of training increases the mean eligibility index of newly selected Old Age Allowance beneficiaries in the treatment wards compared to newly selected beneficiaries in the control group* ***(partial treatment)***

Again, if the provision of data about the elderly in the target group is relevant, the effect size for the complete treatment should be substantially larger than the effect size for the partial treatment. Apart from measuring directly from the survey of newly selected beneficiaries whether and to what extent eligibility and priority criteria are fulfilled, our survey of the local representatives will further contain question on what type of information was used for the selection to identify whether the intervention encouraged them to use information on the people in the target group more systematically.

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 5: *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 and alternatively a task

to rate hypothetical profiles of elderly according to their eligibility, explained in more detail in *Appendix C*.

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 6: *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.

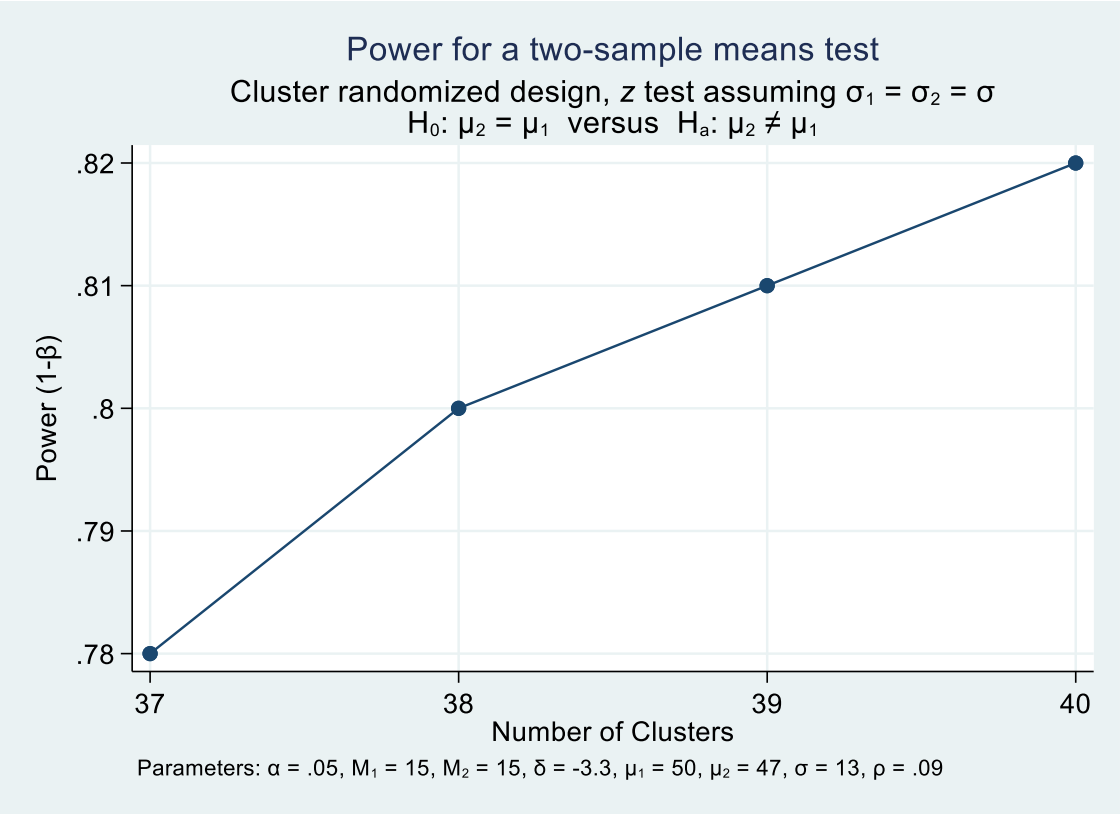
3.3 Sample and power

The study area for this research project covers the rural areas of the Rangpur and Rajshahi divisions in the Northwest of Bangladesh. We exclude urban areas because selection procedures and eligibility rules are very different in urban and rural areas. We further excluded severely flood prone areas because of the expected practical complications for endline-data collection (originally scheduled for August-September 2020). Exclusion of areas was done at the upazila level using spatial data on the level of urbanization and the risk of floods.

To plan this study in terms of number of clusters (in this case unions) and total sample size, we carried out power calculations based on the data collected from newly selected beneficiaries for our formative research (Asri et al., 2020) in May 2018 (see *Appendix A* for further details). This data allows us to estimate the mean and standard deviation of our main outcome variables of interest, and the intra-cluster correlation coefficients (treating each union as a cluster) using 362 observations from 8 unions located in the same region. According to the power calculation, we need 38 unions with 15 observations per union to detect an increase in the PPI of the newly selected beneficiaries in treatment and control unions of 25% of a standard deviation with 80%

power. *Figure 5* displays the resulting power varying the number of unions (x-axis) while keeping the number of observations per union fixed at 15 (five beneficiaries from each of three wards).[10] We further planned that each of the 76 unions has to be located in a different upazila because, as described above, the list of newly selected beneficiaries needs to be approved by the upazila level committee. Further, given the administrative organization of Bangladesh, union level representatives under the same upazila level government frequently interact with each other. Selecting only one union per upazila prevents potential spill-over effects mediated through such interactions.

Figure 5: Illustration of the Power Calculation



Source: Author's illustration using data from Asri et al., 2020.

After excluding urban and severely flood-prone upazilas, 83 upazilas remained in the Rangpur and Rajshahi divisions. In each of these 83 upazilas, we randomly selected one union and collected our baseline data then in 83 unions located in 83 upazilas. Since according to our power calculations described above, we needed 76 unions, we dropped six unions where we could not

[10] We decided on 15 observation in each union as this gives us high power under our feasibility constraints (budgetary and administrative constraints regarding the number of unions).

survey the UP Chairman and one union based on the lowest number of completed baseline surveys.

Initially, we started the implementation of the intervention in these remaining 76 unions from 76 upazilas, 38 randomly assigned to the treatment group and 38 randomly assigned to the control group. For assigning the unions to treatment and control group, we used single random assignment stratified by district, and from every upazila one union was randomly selected. The randomization was done in private by one of the PIs using random number generation in Stata. Balance on covariates was only checked after the random assignment and is reported below. Since we stratified at the district level, we include strata dummies in our main specification (Equation 1; see Bruhn and McKenzie, 2009).

Unfortunately, two unions had already completed the selection of beneficiaries when our trainers were on their way. In response, we identified four unions out of the remaining seven unassigned unions from the baseline where the selection had not been completed, randomly assigned two unions to the treatment and two unions to the control group. The intervention was hence implemented in 40 unions located in 40 out of 80 randomly selected upazilas located in 14 districts. The remaining 40 unions also located in 40 out of 80 randomly selected upazilas are control upazilas. To avoid selection effects, all initially selected unions (including the two non-compliers) plus the additional four unions remain in our sample and we will estimate Intention-to-Treat Effects, as described in the next section.

For the random selection of three wards within each union for the data provision, we took into account that the three women representatives in the selection committee represent groups of three wards. For each UP Women Member, we randomly selected one of the three wards that she represents into the sample for the complete treatment. This ward will also be included in our endline data collection. Additionally, for the endline data collection we will randomly select one of the other two wards represented by each UP Woman Member into the sample of partial treatment. In the control unions, we will select randomly from each UP Women Member one ward for endline data collection. Hence, in total, we will collect data from six wards in each treatment union, i.e. three exposed to complete treatment and three exposed to partial treatment, and from three wards in each control union not exposed to any treatment (see discussion of the endline data collection below).

Given our positive experience with the collection of the data for our formative research (see *Appendix A*) and for the baseline (see next section for details), we do not anticipate that during

the endline data collection we have to deviate from our plans with respect to the sample size. Before starting to survey in any union, we will first collect the ward-specific lists of newly selected beneficiaries from the UP Office. For each ward, we will randomly rank the newly selected beneficiaries and then survey the five beneficiaries with highest rank. In case of unavailability of any beneficiary during survey, we will survey the next ranked person from the list. The protocol will be to visit the beneficiaries' house twice on two separate days before replacing them with the next ranked beneficiary. Based on our experience at baseline (and during our formative research), we also expect to be able to survey more than 90% of selection-committee members. We will follow the same protocol visiting each person's house twice before dropping any union selection committee member. Unfortunately, no replacement is possible here.

4. Data

4.1. Baseline data collection

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 (N=1494). Our team of enumerators managed to interview 92% of them (N=1378). The remaining 8% were either 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.[11] 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.[12] 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

[11] We framed the survey as being about the role of local governments in implementing social safety nets in general and asked the local representatives about the selection rules for three different social safety nets.

[12] The design of the dice game closely follows Fischbacher & Föllmi-Heusi (2013) but was adapted for the phone survey. Respondents counted silently using one hand as counting with one hand until 20 is very common in Bangladesh. We piloted this with many people from different backgrounds and occupations to assure that literally every respondent would find it easy and convenient to count with one hand.

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 & 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 level statistics to check whether our samples are balanced. The balance tables using data from the baseline survey and administrative data at the upazila level are shown below. 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**	**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

Source: Baseline data collected in September-October 2019.

Table 2: Balance check using upazila level statistics

	Control	Treatment	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	
P-value of F-test of joint orthogonality			0.817

Source: Bangladesh Upazila statistics (World Bank, 2016).

4.2. Endline-data collection

The endline-data collection will be focused on capturing whether the intervention improved the targeting of the benefits. We will collect data from newly selected OAA beneficiaries, from union selection committee members and from newly selected Widow Allowance beneficiaries. From the newly selected beneficiaries, we will collect 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 will collect data on personal connections to local representatives and officials now and two years ago. From the selection-committee members, we will collect 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 will collect 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, we plan to interview 5 newly selected beneficiaries for OAA and 5 newly selected beneficiaries for the Widow Allowance. The planned sample sizes are shown in *Table 3* below:

Table 3: Planned sample sizes for endline-data collection

	Treatment unions (N=40)	**Control unions (N=40)**	**Total unions (N=80)**
OAA beneficiaries	1200	600	1800
Selection committee members	720	720	1440
Widow Allowance beneficiaries	600	600	1200

Note: The beneficiaries will be all newly selected beneficiaries according to the lists at the Union Parishad Office.

5. Analysis

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 will follow the below regression model to estimate the intention-to-treat (ITT)[13] effect of the intervention:

$$Y_{ij} = \alpha + \beta T_j + \gamma X_j + \varepsilon_{ij}, \qquad (1)$$

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 ε_{ij} is the standard error clustered at the union level. As a robustness check, we will also estimate the outcomes without baseline covariates.

As covariates in regression model (1), we will include baseline values of local representatives' average knowledge index of OAA rules, their average honesty score, their reading ability, strata

[13] As two unions in the treatment group had already completed their selection of new beneficiaries (see Section 4.3), we have a non-compliance rate of 5%.

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. According to McKenzie (2012), controlling for such baseline variables is expected to improve our power. However, we did not take this into account to assess our power rather conservatively. We will 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 will adapt the regression model as follows:

$$Y_{ij} = \alpha + \beta T_j + \gamma X_i + \varepsilon_{ij}, \qquad (2)$$

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 ε_{ij} is the standard error clustered at the union level. We will now 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 will also estimate the regression model without baseline covariates.

As the outcome variables are indices (the PPI, the knowledge index and the eligibility index), we do not expect any outliers. In case of missing values, we will check the robustness of the results by imputing with the mean, the lowest and the highest value of the respective variable.

As mentioned above, we will 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 will then yield 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.

Heterogeneous Effects: We plan exploratory analyses of whether the impact of the intervention depends on the preference for corrupt behaviors of local representatives in charge. One could expect that training and data provision are highly effective in areas where local representatives want to target those who need the pension the most and want to follow the eligibility guidelines by the national government. However, one could also expect that both intervention components are completely ineffective in areas in which local representatives want to continue targeting social

pension benefits according to their own preferences including corrupt practices. We will therefore complement the equations (1) and (2) with interaction terms of the treatment indicator and the average dice score of the local representatives to test whether the impact of the intervention varies with the preference for (dis)honesty.

Potential limitations: Certainly, this research design is not without limitations. Wards are relatively close to each other and representatives who received training but no data for their ward might have observed the provision of data in a neighboring ward. We therefore may overestimate the impact of training alone (i.e. of the partial treatment) if local representatives from wards where only training was provided collect data by themselves following what they have observed in terms of EIC filling on other wards in the union. Also due to the potential spill-over effects, we may underestimate the impact of the complementary data provision measured by the difference between the complete treatment impact and the partial treatment impact.

Additionally, local representatives in wards that received training and data may not use the data for different reasons. Our research design is built in such a way that we compare treatments ward always to control wards keeping these potential issues in mind. We will further design the endline-data collection in such a way that it allows us to assess whether local representatives started collecting their own data or refrained from using the provided data.

6. Interpreting Results

Our study design allows us to shed light on the role of state capacity for the targeting of a large-scale social transfer program and on how the targeting performance could potentially be improved. In case the intervention increases the PPI of newly selected beneficiaries and is thereby better targeted towards the poor, this would suggest that weak state capacity was indeed a major constraint. In case the intervention does not improve the targeting performance, this would suggest that other factors, such as corruption, are the key drivers and that interventions focusing on accountability or incentives might be more promising. We have further information (e.g. through the results of the dice game) to provide at least exploratory evidence for such alternative channels.

Further, our research design allows us to distinguish between the effects of different types of capacity enhancing interventions, namely the impact of providing training and data (complete treatment) and the impact of providing training only (partial treatment). If only the former is effective, it will become clear that training as well as data are lacking in the current situation. If

providing only training is effective as well, and with similar effect size, it would suggest that local representatives were only lacking knowledge on national guidelines and their local knowledge can substitute the formally provided data. In that case, we may be able to compare the costs and benefits of providing both training and data with providing training only to provide guidance for future reforms.

Referring to our research hypotheses stated above, depending on which outcome variable shows an impact of the intervention, we can draw different implications for future policymaking and reforms:

Starting with our primary outcome of interest, an increase in the PPI would suggest that due to the intervention local representatives in treatment areas are better able to target the poor among the elderly compared to control areas. If we further see an improvement in the secondary outcome of interest, the eligibility index, this would show that local representatives applied the selection criteria. In terms of the underlying channel, an increase in the knowledge index would show that the local representatives internalized the national guidelines for the selection of beneficiaries. In case the eligibility index did not improve and the knowledge index did not improve either, this would suggest that they continued using their own ways of assessing poverty instead of the nationally prescribed eligibility rules. And similarly, instead of the provided data on EICs, they use the locally available information on potential beneficiaries to make a selection which is still aligned with targeting the poor.

A potentially relevant and interesting scenario could be that the PPI improves, the knowledge index also improves but the eligibility index does not improve. This would suggest that local representatives have internalized the selection rules but do not apply them for selection. This may be due to disagreement with the selection rules, or it could be due to lack of data in the wards that did not receive target-group data provision. In the former case when there is overall disagreement with the selection rules prescribed by the national government, the provision of Eligibility Information Cards can only help to some extent. However, on the part of local representatives as PPI improved this would still suggest an overall willingness to target the poor and an understanding of the general objective of the scheme.

Another potential scenario could be that the PPI improves, the knowledge index does not improve but the eligibility index improves. This would suggest that local representatives have internalized the objectives of the selection rules and were able to apply them but cannot remember the rules as they are written in the national guideline. It is also possible that they followed the selection

rules by taking help from other sources such as other members of the committee. However, in both the scenarios it is evident that the training of the selection rules improves targeting. Improvement in eligibility index in the wards without data provision again will indicate that selection committee members' local knowledge along with the training on national guideline is sufficient for improved targeting.

Finally, an improvement either in knowledge or eligibility index or in both of them without an improvement in PPI will show that national guidelines clearly fall short in targeting the poor among the elderly and that nationally prescribed guidelines are not well aligned with other more general poverty measures.

In terms of indirect impact, if the targeting of the Widow Allowance improves, this would show that the intervention enabled local representatives to acquire skills which they can also apply to other schemes. For instance, with respect to assessing poverty and or systematic selection procedures. However, if the targeting of the Widow Allowance does not show any improvement due to the intervention, this would mean the local representatives applied the additional knowledge and skills only to the OAA and may require either a more comprehensive training module on social safety nets in general or a training for each of the schemes.

Either way, the results would help filling the knowledge gap on the importance of state capacity for social policy targeting in developing countries and on the effectiveness of an intervention designed to increase state capacity in an inexpensive and easily scalable manner. Given the importance attributed to local governance in the development literature, our study is of relevance and interest not only for policy makers but, very much so, also for the research community.

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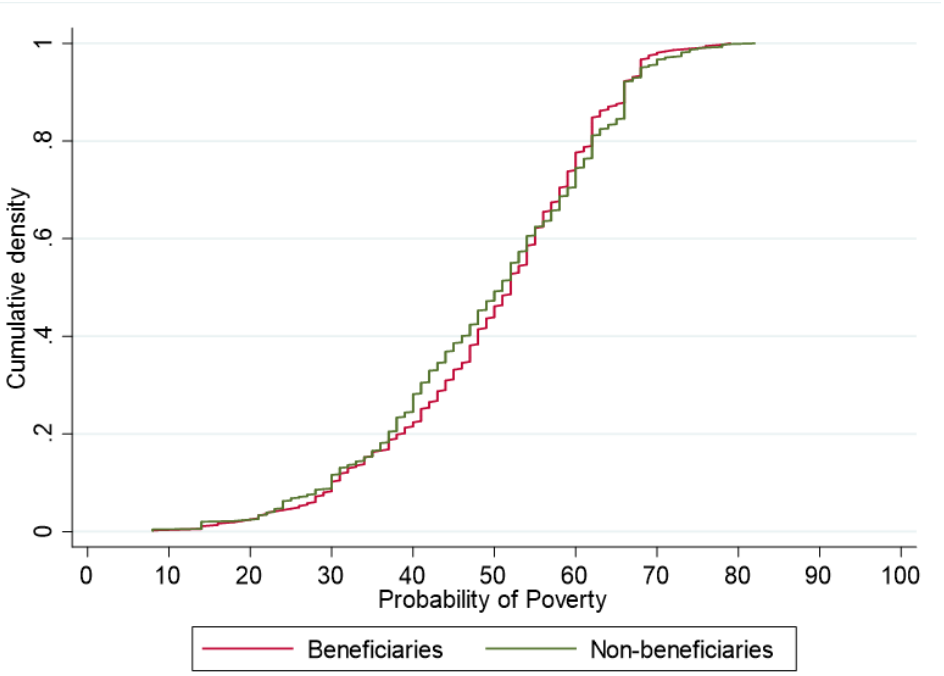
8. Appendices

Appendix A: Formative research data

In our formative research, we present evidence on the extent and possible causes of mistargeting of the Old Age Allowance in Bangladesh. The evidence stems from surveys and lab-in-the-field experiments that we ran in eight different unions (municipalities) with three different groups: (i) a random sample of the elderly population (potential beneficiaries), (ii) a random sample of newly selected beneficiaries, and (iii) the local government representatives, who were in charge of the last round of selections. We find massive mistargeting in both districts. Most strikingly, the distribution of the poverty probability index (PPI) are almost identical for non-beneficiaries and the newly selected beneficiaries (see *Figure A.1* below).

Since we use the data from our formative research for the power calculations for the randomized controlled trial, we describe in the following the data collection in more detail. In two districts in the Northwest of Bangladesh, we randomly selected four upazilas and one union in each of them. Hence, in total we carried out the data collection in eight unions from eight upazilas located in two districts. We conducted a survey of newly selected OAA beneficiaries (N=362) and of a general elderly sample (mostly non-beneficiaries) (N=853) and another survey of local representatives and officials (N=95). For the beneficiary survey, we randomly sampled five beneficiaries from each ward from the union's beneficiary list of the last two rounds of beneficiary selection. For the general elderly sample, we randomly sampled 12 elderly persons (non-beneficiaries) from each ward within a union (in each union, there are nine wards). For the local government survey, we interviewed all Union Parishad members, which is composed of nine ward representatives in each union and the Union Chairman. In addition, we interviewed the Union Secretary and the Union Social Worker; both are administrative positions in each union dealing with the implementation of social safety nets. See Asri et al. (2020) for more details on our formative research. Our power calculations are based on the data from the elderly survey.

Figure A.1: Probability of poverty index of non-beneficiaries and beneficiaries



Source: Asri et al. 2020.

Appendix B: Details on intervention

Table A.1: Detailed description of both intervention components

Item No		Item	
Brief name			
1	Write the name	Training Old Age Allowance selection committee members on the beneficiary selection criteria and procedures	Filling Eligibility Information Cards for the elderly and transferring the same cards to the Old Age Allowance selection committees
Why?			
2	Describe rationale	As many local representatives in charge of selecting new beneficiaries for the Old Age Allowance are not informed about the national guidelines for eligibility, ARCED Foundation in collaboration with the Department of Social Services provided a training program. The objective was that in the future, local representatives can apply the guidelines learnt in the training and will select the most vulnerable among the elderly.	To make a systematic selection of beneficiaries, union selection committee members lack data on the people in the target group. Filling out Eligibility Information Cards and transferring these EICs to the union selection committee has the primary purpose of informing selection committee members about the elderly in the target group of the Old Age Allowance. The Eligibility Information Card contains all the relevant information on an elderly person that needs to be considered to make a systematic selection of beneficiaries in the area.

What?			
3	Materials	Tablets with videos stored on them, training protocol to review content, quiz, boxes, example eligibility information cards, handout **Description of video plot:** The video starts by explaining the objective of the Old Age Allowance. Afterwards, it shows a UP Chairman sitting together with the other Old Age Allowance beneficiary selection committee members. As the chairperson of the committee, he reads aloud a letter from the Ministry of Social Welfare. The committee is requested to select new beneficiaries for the Old Age Allowance. The UP Chairman is shown thinking about the challenge of selecting a few elderly among many poor elderly and is then shown using the newly introduced Eligibility Information Card and three colored boxes in green, yellow and red to make a systematic selection of beneficiaries jointly with the other members of the Old Age Allowance Committee. The selection is then approved by the upazila level committee and the video shows newly selected beneficiaries collecting their pension benefits.	Old Age Allowance Information Cards, calculator for land and income calculation, tablet with app for age calculation, waiting numbers for managing the crowd.
4	Procedures	Steps as presented in the protocol for trainers: Step 1: Meet Upazila Social Service Officer, Union Social Worker and UP Chairman Step 2: Meet the UP Members of the wards where EIC filling will take place. Identify a suitable venue for EIC filling.	Steps as presented in the protocol for filling EICs: Step 1: Confirm preparations with trainer over the phone Step 2: Receive detailed information from trainer Step 3: Meet UP Chairman and UP Secretary Step 4: Meet the three UP Members from selected wards Step 5: Monitor miking

		Step 4: Make appointments with the selection committee members for training. Step 5: To prepare EIC filling, communicate with the miking vendor Step 6: To prepare EIC filling, monitor miking before the field officers for EIC filling arrive. Step 7: Provide training to the selection committee members Step 8: Handover all relevant information to the EIC filling team	Step 6: Confirm table and chair arrangement Step 7: Visit locations for EIC filling and ensure local support Step 8: Set up the booth Step 9: Welcome all attendees and manage waiting people Step 11: Fill ICs Page 1: Identifying information Page 2: Other benefits from government or NGOs (ineligibility criterion), eligibility criteria incl. having national ID, birth certificate, being a permanent resident of the union, being at least as old as the eligibility age (62 years for females and 65 years for males) and household's annual per capita income of less than 10'000 BDT. Page 3: Priority criteria namely physical condition, age of the elderly, economic and social condition Page 4: Household ownership of durable assets, housing materials, electricity, bank account, signatures by field officer and elderly person. Step 12: Make photocopies for Dhaka office Step 13: Hand-over ICs to the Union Secretary

Who provided?			
5	Intervention provider	Trainers - Master graduates primarily from Social Sciences - Competitive selection process, with interview and mock-test - Final selection was done after observing performance during field practice - Important skills: able to communicate clearly, able to explain rules, very good manners when dealing with local representatives, previous field experience - All male trainers due to the requirement of travelling alone and frequently and also after sunset at times. - Received 5 days long training including two field practice days. - During field practice days, trainers trained local representatives and were observed by the monitoring team for feedback and selection of supervisors.	Field officers for EIC filling - BA/MA degrees - Long working experience in data collection - Patient with elderly respondents - All male trainers due to the requirement of travelling frequently and also after sunset at times. - Received 3 days long training including one day field practice. - During field practice, filled EICs for elderly, transferred EICs to UP Secretary and were observed by the monitoring team for feedback and selection of supervisors.
How?			
6	Mode of delivery	One-on-one training using 10 videos that explain the guidelines to select the beneficiaries for the Old Age Allowance following the protocol (see the video plot below). Training also includes using two sets of pre-filled Information Cards as samples. The first set was used during training in order to ensure that the trainee understands the concepts properly. The second set was used as a practical exercise in the end of the training.	Field officers fill out the Eligibility Information Cards for the elderly. They give the original to the elderly person, fill out one copy and transfer it to the selection committee to provide data on the elderly in the target group to the selection committee members.

Where?			
7	Location	40 unions in rural areas of Rangpur and Rajshahi divisions in the Northwest of Bangladesh. Each union is located in a different upazila. The training typically took place either at the Union Parishad Office or at the home of the local representatives. As per protocol, trainers were not allowed to give the training in the open and had to send curious observers away to mitigate any distraction from the training.	40 unions in rural areas of Rangpur and Rajshahi divisions in the Northwest of Bangladesh. Each union is located in a different upazila. Filling of EICs took place in 120 wards (3 per union). Field officers were requested to select easily accessible public places in the randomly selected wards at which people of any gender and religion would feel comfortable. Commonly selected places were primary schools.
When and how much?			
8	Number of sessions, schedule, duration, intensity, dose	Each selection committee member received the same training individually. Each training lasted between 40 and 90 minutes but most trainings took 60 minutes. At the end of the training the local representatives received a hand-out summarizing the training content.	Filling of EICs took place once on a pre-scheduled date from 8 am in the morning until 6 pm in the evening.
Tailoring			
9	Was the intervention personalized or adapted?	The content of the training was the same for every training participant, but trainers offered to show a video again and gave more time to people who needed more time to understand or had more questions.	Field officers always requested the same information from the elderly but they were trained to collect all the information in a rather conversational mode and to give more time to elderly who struggled to speak or hear. In other cases, for instance when adult children provided all relevant information on the elderly parent, they were able to proceed faster but also sticked to the conversational mode.

Modifications			
10*	Was the intervention modified?	No modification	No modification
How well?			
11		The intervention was delivered as planned.	The intervention was delivered as planned.

Appendix C: Description of indices

i. Probability of poverty index (PPI)

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

ii. 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

iii. Knowledge index

During endline-data collection, the selection committee members will be asked questions on the eligibility and priority criteria for the Old Age Allowance as well as questions on procedural aspects of the selection of beneficiaries. Based on correct/incorrect responses, we count the number of

correct responses indicating the local representative's knowledge of eligibility criteria, priority criteria and procedural selection rules. The following questions are example questions for constructing such an index. The exact composition of the knowledge index will be finalized after piloting the questionnaire in the field in November/December 2020 (or as soon as COVID19 pandemic permits).

- What is the minimum age for a female elderly to be eligible for OAA?
- What is the maximum annual per capita income of the household of an applicant to be eligible for OAA?
- What is the threshold for landless?
- Which economic conditions are considered for prioritization?
- Which social conditions are considered for prioritization for a female applicant?
- What disqualifies an elderly applicant from being considered as eligible for the Old Age Allowance?
- Who belongs to the beneficiary selection committee?

9. Administrative information

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Institutional Review Board (ethics approval):

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Declaration of interest:

The authors declare that they have no conflict of interest.

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