Targeting Ultra-poor Households in Honduras and Peru

Dean Karlan and Bram Thuysbaert

For policy purposes, it is important to understand the relative efficacy of various methods to target the poor. Recently, participatory methods have received particular attention. We examine the effectiveness of a hybrid two-step process that combines a participatory wealth ranking and a verification household survey, relative to two proxy means tests (the Progress out of Poverty Index and a housing index), in Honduras and Peru. The methods we examine perform similarly by various metrics. They all identify most accurately the poorest and the wealthiest households but perform with mixed results among households in the middle of the distribution. Ultimately, given similar performance, the analysis suggests that costs should be the driving consideration in choosing across methods. JEL codes: C81, O12, O20.

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Effectively identifying the appropriate recipients for aid programs is critical in order to maximize social impact with scarce resources. The erroneous inclusion of a household that is not part of the target population generally means resources wasted. Yet effective targeting is not costless. In theory, the economics are straightforward: screen such that the marginal cost of screening out the marginal ineligible participant is equal to the wasted resources transferred as a result of mistargeting.

Yet targeting poor households is difficult because the criteria for eligibility may be hard both to define and to verify. As there is no single defining characteristic of poverty, criteria for eligibility tend to be multidimensional and subject to

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much debate. Poverty lines based on per capita income or expenditure are often used, but it is also well recognized that they have limitations and represent a simplification of what it means to be poor (Ravallion 1998; Bebbington 1999; Alwang, Siegel, and Jorgensen 2001).

Once the relevant criteria are defined, verifying that certain households meet those criteria poses its own challenges. Measuring income for poor families, for example, is notoriously challenging: it derives mostly from informal sources and is often in kind rather than monetary (Deaton 1997). Verification may be further complicated when respondents, wishing to participate in the program, perceive an incentive to misreport information. Such challenges may create a trade-off between accuracy and cost in identifying eligible households.

The challenges of verification require cost-effective solutions to targeting particular households. Three methods have been broadly proposed as solutions (Coady, Grosh, and Hoddinott 2004). First is geographic targeting, which uses national or regional poverty maps to select eligible households by region. While typically less precise relative to other methods, geographic targeting may suffice as an inexpensive and quick method in certain circumstances. Even when other selection methods are used, geographical targeting is often applied as a first filter. A second method is a proxy means test (PMT), in which field workers collect demographic, asset, or housing information that can be used to approximate a household's poverty status. Compared to measurements of income or consumption, the inputs required for a PMT are both quicker to collect and easier to verify. However, for any PMT there is a substantial risk of targeting error. Moreover, PMTs typically lack transparency, potentially leading to accusations of favoritism or incompetence, which could undermine the legitimacy of the program. A third method is selection by village members themselves. The criteria for selection can range from nomination by local leaders to ranking through a participatory wealth ranking (PWR). A PWR invites village members to rank members of their community according to poverty levels. The poorest members, typically, are then eligible for the program. The increasing popularity of PWRs reflects a broader trend toward participatory rural appraisals (PRAs) to collect information and design aid programs (Chambers 1994). Such participatory processes have the advantage of transparency and the incorporation of local knowledge, which is likely to be more precise than a PMT. On the other hand, there are a number of reasons why a PWR may not work well in practice. Local elites may manipulate the participatory process in order to include themselves, their family or members of a particular group. Moreover, local definitions of poverty may differ from the criteria of the program implementer.

We examine the effectiveness of a three-step "Targeting the Ultra-Poor" ("TUP") process relative to other methods in two different contexts, Honduras and Peru. The TUP method combines geographical targeting, PWRs and PMTs; we concentrate especially on steps two and three in this paper. The process was used to determine eligibility for the CGAP-Ford Foundation Graduation Program, a multifaceted livelihood program evaluated in six countries (the two here, plus Ethiopia, Ghana, India, and Pakistan). The average impact across all six sites was strong on almost all outcomes (consumption, income, assets, mental health, etc.), although the Honduras site did not generate the same consistently positive impacts. The impact evaluation is reported in Banerjee et al. (2015). In Gracias, Honduras, the program was implemented in 2008 by Plan International Honduras and ODEF Social. In Cusco, Peru, the program was implemented in 2010 by Plan International Peru and Asociación Arariwa. The programs aim to tackle extreme poverty by combining an asset transfer (e.g., livestock) with training, cash transfers, and health services.

In both countries, the first step used geographical targeting. The intervention area was determined by the local organizations' area of operations and reference to regional poverty maps; villages were then selected using a simple scorecard. This paper does not evaluate the accuracy of this first step of identifying the broad geographical areas. The second and final steps, the focus of our analysis, was a PWR in the villages to determine the poorest households, and then a verification survey by the NGO that confirmed program eligibility and basic economic status questions. Our analysis uses data from a detailed household survey that was administered after the targeting process. The survey included the selected (i.e., identified as ultra-poor) households, as well as a random sample of nonselected ("excluded") households in the same village. In Honduras, 423 selected and 637 excluded households were surveyed in 15 randomly selected villages; In Peru, 470 selected and 537 excluded households were surveyed in 21 randomly selected villages.

Section 1 of the paper describes the program and the targeting process in both sites. The sample and data used for the subsequent analysis are described in section 2. Section 3 compares the selected and excluded households at each stage in the targeting process across a range of variables in each country. Section 4 compares the accuracy of the TUP targeting process to two simple PMTs—a housing index and the Progress out of Poverty Index (PPI)—first using per capita consumption as a benchmark of true poverty and then looking at an asset index as a benchmark. Section 5 compares the performance of the TUP targeting process, the housing index and the PPI using other metrics of poverty such as livestock value and vulnerability. Section 6 examines the characteristics that predict a household's ranking in the PWR in a regression framework. Finally, section 7 summarizes our results and discusses the policy implications.

I. The Program and Targeting Process

CGAP-Ford Foundation Graduation Program, aims to help the poorest families "graduate" from extreme poverty within a 24-month period. The program targets the most extreme poor with a multifaceted program with six elements: productive asset transfer, consumption support in the short term, access to savings services, skills training, household visits with coaching support, and health services or products. Six randomized trials were conducted in a coordinated effort

(Banerjee et al. 2015). In two of these sites, Honduras and Peru, we built in additional data collection from the entire village, not just the identified participants, in order to analyze the targeting process.

The Honduras program is operated by Plan International Honduras and a local microfinance institution, ODEF Social, in the northern districts of Lempira department. Lempira was chosen as the intervention zone because of the high incidence of extreme poverty and because Plan already had projects in the area. The Peru program is operated by Plan International Peru and a Cusco-based microfinance institution, Asociación Arariwa, in two southern provinces of the Cusco department, Canas and Acomayo. As in Honduras, the intervention zones were selected according to poverty indicators and the existing presence of the local organizations.

In both sites, the program implementers first selected the poorest 80 villages in the intervention zone.[1] In Honduras, the Plan team already had considerable experience working in the area and selected the villages based on their prior observations and perceptions. In Peru, where prior knowledge of the project zone was more limited, the Plan team selected villages based on a simple scorecard that assessed access to basic services like roads, electricity, water, education, and healthcare. Thus village size was not considered directly, and villages that were on average lacking basic services were systematically included in the target.

Within selected villages, households were chosen using a two-step process. The first step was a PWR to which all village members were invited. Households selected in this step progressed to the second step, a short verification survey applied by Plan field workers that was used to confirm eligibility according to country-specific criteria. For program impact evaluation, the villages were then randomly assigned to treatment and control groups; within treatment villages selected households were also randomly assigned to treatment and control groups. Details of each step of the targeting process are described in the subsections below.

The Participatory Wealth Ranking

All village members were invited to attend the PWR, which followed the geographical selection of eligible villages. In Honduras, the invitation was sent through local schools. The students informed their parents of the meeting that would take place in the school the following day. In Peru, Plan field workers went to each village a month prior to the meeting to set a date and invite participants. In both countries, field workers stressed the importance of a high level of participation and the attendance of women as well as men. In Peru, field workers would go ahead with meeting if more than 50% of households were represented, which, in most of the villages of the zone, is the established threshold at which communal decisions can be taken; in Honduras, the threshold was lower. Monitoring visits conducted by our research assistant at five of the meetings in

1. In Peru, an additional six villages were later added, bringing the total to 86.

Peru suggest that male participants typically outnumbered female participants by about three to one, although in other cases only women participated due to a misunderstanding of the meeting's aims. Comments from participants indicated that those who lived furthest away, typically the poorest households, were under-represented at the meetings. While there is a risk that such households were less likely to be correctly identified as ultra-poor, there is nothing that suggests they were at any greater risk than other households not present, particularly if common knowledge of their poor welfare was expressed in the meetings. However, with the goal of representative attendance at meetings, extra costs may be necessary in the future to ensure high participation of households living furthest away from meeting locations.

Each village PWR meeting was run by three field workers in a common area of the village and lasted between two and three hours. In Honduras the meetings were conducted in Spanish, while in Peru most meetings were conducted in a mix of Quechua and Spanish, with some field workers speaking more in Quechua and others more in Spanish. The monitoring visits in Peru suggested that the level of participation, particularly among women, was higher when the meeting was predominately conducted in Quechua. After a brief introduction to the implementing organizations and the targeting process, participants prepared a sketch map of the village.[2] The map included landmarks such as roads, rivers, the school, village hall, and different neighborhoods. In Honduras the facilitator attempted to engage all members, but in practice only two or three people tended to participate in the production of the map, while in Peru a group of four people was selected to work on the map while the other village members began the wealth ranking. In parallel, other village members assisted a field worker in preparing index cards with the names of all the household heads in the village.

In Honduras, the ranking process began with a comparison between two families. For the first two households, the field worker read out the name of the household heads and then asked the village members if the two households lived in the same conditions. If so, the two index cards were placed in the same pile. If one lived better than the other, they were placed in separate piles. The field worker then picked up a third index card and asked if this household lived in similar, better, or worse conditions than the first two households. The process continued until all of the households were classified in piles. The number of categories varied between villages, depending on the responses of the village members. In homogenous villages, it was possible that the majority of households were categorized in the same group, although in such situations the field worker tried to encourage participants to identify subtle differences. The criteria used to distinguish between categories were implicit, rather than formally defined.

2. In Honduras, no mention was made of the Graduation Program in order not to bias participant behavior in the PWR. In Peru, participants were given information only about the training elements of the project. The cash consumption stipend and asset transfer were not mentioned.

In Peru, on the other hand, the ranking process began with the definition of the wealth categories. The field worker proposed to the village members that in every village there are "families that have the most," "families that have neither a lot nor little," "families that have little," and "families that have the least." In many cases, the initial reaction of the meeting participants was to argue that everyone in the village is equally poor. However, with the use of examples, the field worker was able to demonstrate to the participants that although all may be poor, some are poorer than others.

Next, the village defined four wealth categories in terms of land, animal ownership and the house characteristics. For example, "families that have the most" might be defined as those that have more than 50 sheep, eight cows, or 10 llamas; more than three *masas* of land; and a house with four or more rooms. The "families that have the least" might have fewer than 14 sheep, two cows, or three llamas; 0.5 *masas* of land; and a one-room house. Anecdotal evidence suggests that this rather abstract exercise was difficult for many participants, and significant guidance was required from the case worker to produce a logical classification.

Index cards with the name of the household heads were then read out in random order. The location of the household was drawn on the village map, and the participants decided in which category the household belonged. The index card was then placed in a cardboard box corresponding to that category. This process created a number of challenges. First, it was a time-consuming process, particularly in large villages, and participants evidently tired toward the end. Second, there was no established process for handling disputed cases, where some village members felt that the household should be in one category and others felt otherwise. Given the time constraint, the field worker needed to make a quick decision and would typically go with the option that was being voiced most loudly, or appoint the village president to act as arbitrator. In general, there was little reference to the objective criteria established by the participants, and it was unclear whether the classification of households reflected these criteria or not.

With the ranking complete, the next step at both sites was to determine the PWR categories that would be eligible for inclusion into the program. In practice, the norm was to select the poorest two categories from each village, which was normally over half of the households in the village. In poorer villages, the three poorest categories were selected.[3]

The Verification Step by NGO Field Workers

The next step of the TUP targeting process was a verification survey for households selected in the PWR. This was conducted by the NGO field workers at each house or in a community meeting. During the survey process, case workers

3. In a few villages in Honduras, four categories were selected.

would sometimes encounter additional households that had either not been ranked in the PWR or who claimed they had been ranked incorrectly and would include these households in the survey. Not all households selected in the PWR were surveyed: some had migrated from the community, others were not at home, and still others did not meet the inclusion criteria defined for the project. The first aim of the verification survey was to verify the suitability of the household for the project. We label the criteria used for this purpose the "programmatic" criteria. In Honduras the criteria applied were (1) the household includes a child under the age of 18 to meet Plan's mission of helping children and (2) the household has lived in the village for at least three years. In Peru the criteria applied were (1) the head of the household or their spouse is younger than 60 and would therefore be capable of managing an enterprise for several years to come; (2) the household includes a child under the age of 18; and (3) the household head doesn't live outside the community for more than six months of the year.

The second aim of the verification survey was to confirm that the household was indeed poor, in order to correct for errors or manipulation during the PWR: we label these "poverty" criteria. In Honduras, this took the form of two criteria: (1) the household has a monthly per capita income of 600 Lempira or less, the monthly cost of a basic food basket and (2) the household meets at least two of the following three criteria: (a) having one manzana or less of land under cultivation[4]; (b) having minors in the household who work in income-generating or productive activities; (c) not currently participating in a development program. In Peru, four criteria were used, including a PMT: (1) neither the household head nor the spouse have a formal profession or occupation; (2) the household head does not own a second home outside of the community; (3) the household does not currently borrow money from formal sources[5]; (4) the household has a PPI score of 30 or less. The PPI was chosen as a PMT method because it was well tested in Peru and simple to apply and calculate. With a PPI score of 30 or more, there is a 50% probability that the household is not below the national poverty line (Schreiner 2009).

One concern with the verification step is that participants may have answered self-reported measures strategically to remain included through this stage of targeting; however, within a two-step targeting process it is difficult to control how honestly people will participate after being selected for program inclusion in the first step. Additionally, we recognize that using NGO workers instead of the government may have affected the verification step, as well as the PWR— participants may respond differently based on the implementing party. However, this variation is determined by the relationship of the villagers to the implementing party and is a risk regardless of the party being an NGO or the government.

4. One manzana equals about 1.7 acres or 0.7 hectare.

5. Households that had a loan with the microfinance institution Caja Nuestra Gente, which had recently entered into an agreement with the government to provide credit to beneficiaries of the conditional cash transfer scheme, Programa JUNTOS, were not excluded.

II. Sample and Data

After the targeting steps were complete, we randomly selected 15 villages (out of 40 treatment villages) from Honduras, and 21 villages (out of 40 treatment villages) from Peru to be included in the targeting analysis study. Within each of these communities, an extensive socio-economic survey was administered to the selected households as part of an impact evaluation study. In addition, for the purpose of this targeting analysis, we also surveyed a random sample of the excluded households. Since we sampled those selected for the program at a higher rate than those not selected for the program, we use sampling weights throughout the analysis to make the sample representative at the village level. In the 15 selected communities in Honduras, a total of 1,060 households were surveyed—423 selected households and 637 nonselected households, whereas in the 21 villages in Peru 470 selected and 537 nonselected households were surveyed, for a total sample of 1,007 households.

Two filters were applied to define the sample frame for analysis. First, as mentioned above, several "programmatic" criteria were applied in the verification step (e.g., presence of a child under 18 in the household). These programmatic criteria reflect the priors of the implementing organizations about which types of households are suitable for the intervention and do not necessarily relate to poverty. To focus on how well the targeting methods select the poor, we therefore remove from the sample all households that do not satisfy the programmatic criteria.[6]

Second, some households identified as poor in the PWR were not surveyed later in the verification step. In some cases, there was no respondent available when the NGO field workers returned to the community. In other cases, the household could not be located in the community. For these households, we do not know whether, had they been surveyed, they would have been selected or not. Since we are interested in understanding how each of the steps contributed to the final selection, we discard from the sample the households that were identified as poor in the PWR but were not verified by the NGO in the verification survey. After applying these two filters, we are left with 897 households in the analysis sample in Honduras and 717 households in Peru (table 1).

Of the 897 households in the Honduras sample, 702 were categorized as ultra-poor at the PWR stage. This corresponds to 62% of households (using sampling weights). Of these, relatively few failed to pass the verification step by the NGO (67 households or 17%).[7] Overall, the two-step TUP targeting process selected 52% of households for the program (conditional on meeting the programmatic criteria). In Peru, 64% of households were identified as ultra-poor at the PWR step, and of these, only 14% were excluded at the verification step. In all, 59% of households in Peru were finally identified as ultra-poor and selected

6. Since we do not have data from the verification survey for the households excluded in the PWR step, we check programmatic eligibility using our household survey data.

7. From table 1, (62%−52%) / 62% = 17%.

Table 1. Description of sample - Peru and Honduras

Honduras		Number of households	% of sample (using sampling weights)
	PWR step		
	Total households in analysis sample	897	100 %
	Considered non-poor in the PWR	195	38 %
	Considered poor in the PWR	702	62 %
	Verification step		
	Finally selected	635	52 %
Peru			
	PWR step		
	Total households in analysis sample	717	100 %
	Considered non-poor in the PWR	154	36 %
	Considered poor in the PWR	563	64 %
	Verification step		
	Finally selected	536	59 %

Source: Authors' analysis based on own data collected.

for inclusion into the program. Table 1 maps the incremental sample size changes from the analysis sample to final selection for the two countries. The final selection rates in Honduras and Peru—52% and 59%, respectively—may seem high, but note that the program villages were purposefully selected because of their high incidence of extreme poverty.

III. Selection at Each Stage of the TUP Process

We begin our analysis by examining differences between how households are categorized at each step of the TUP targeting process. Table 2 (Honduras) and table 3 (Peru) show the means of several welfare indicators for each group at a given step. We compare the groups in terms of demographics and education (panel A), household assets (panel B), productive assets and income (panel C), and consumption, poverty, and vulnerability (panel D). The number of households in each step is displayed in the last row of the table. The combination of the two sample sizes listed under the "PWR step" is the analysis sample for that country, while the combination of the sample sizes listed under the "Verification step" is the total number of households selected in the PWR for that country.

Participatory Wealth Ranking

In both countries, households selected by the PWR are consistently poorer across a range of welfare indicators than households excluded in the PWR. In columns 1–3 of tables 2 and 3, we see that all statistically significant differences between those excluded and selected by the PWR (N = 563 for Peru, N = 702 for

TABLE 2. Selection at each stage of TUP targeting process - Honduras

	PWR step			Verification step			Final selection	Contributions to final selection (%)	
	(1) Excluded (SD)	(2) Selected (SD)	(3) Difference (SE)	(4) Excluded (SD)	(5) Selected (SD)	(6) Difference (SE)	(7) Difference (SE)	(8) PWR step	(9) Verif. Step
Panel A: Demographics and education									
Female-headed household	0.11	0.14	−0.03	0.15	0.14	0.01	−0.02	114 %	−14 %
	(0.31)	(0.35)	(0.03)	(0.36)	(0.35)	(0.05)	(0.02)		
Years of education of household head	1.28	0.84	0.43	0.92	0.83	0.09	0.37	91 %	9 %
	(1.02)	(0.66)	(0.08)	(0.78)	(0.64)	(0.10)	(0.07)		
School enrollment (boys: 12-17 years)	0.54	0.39	0.15	0.61	0.36	0.25	0.19	70 %	30 %
	(0.50)	(0.50)	(0.05)	(0.49)	(0.48)	(0.11)	(0.05)		
School enrollment (girls: 12-17 years)	0.59	0.44	0.15	0.44	0.43	0.01	0.12	97 %	3 %
	(0.49)	(0.49)	(0.06)	(0.50)	(0.50)	(0.09)	(0.05)		
Panel B: Household assets									
Household has radio	0.82	0.71	0.11	0.74	0.70	0.04	0.10	85 %	15 %
	(0.39)	(0.45)	(0.03)	(0.44)	(0.46)	(0.06)	(0.03)		
Household has bicylce	0.26	0.14	0.12	0.12	0.15	−0.02	0.08	109 %	−9 %
	(0.44)	(0.35)	(0.04)	(0.33)	(0.35)	(0.04)	(0.03)		
Asset index	1.90	−0.15	2.05	0.27	−0.23	0.50	1.78	90 %	10 %
	(2.78)	(1.75)	(0.22)	(1.77)	(1.74)	(0.24)	(0.19)		
Latrine with water or septic tank	0.73	0.41	0.33	0.57	0.38	0.20	0.32	79 %	21 %
	(0.55)	(0.56)	(0.05)	(0.59)	(0.55)	(0.08)	(0.04)		
Housing index	1.12	−0.30	1.42	−0.01	−0.36	0.35	1.24	90 %	10 %
	(1.56)	(1.14)	(0.12)	(1.20)	(1.11)	(0.08)	(0.04)		
Panel C: Productive assets and income									
Total cultivated land (m2)	9632	5521	4111	6892	5244	1648	3797	85 %	15 %
	(12527)	(8347)	(1033)	(6680)	(8622)	(945)	(870)		
Number of cattle	0.50	0.08	0.42	0.06	0.08	−0.02	0.32	102 %	−2 %
	(1.61)	(0.69)	(0.12)	(0.32)	(0.74)	(0.05)	(0.10)		
Number of sheep/goats	0.02	0.04	−0.02	0.08	0.03	0.05	0.00	−1650 %	1750 %
	(0.14)	(0.29)	(0.01)	(0.36)	(0.27)	(0.04)	(0.02)		

(Continued)

TABLE 2. *Continued*

	PWR step			Verification step			Final selection	Contributions to final selection (%)	
	(1) Excluded (SD)	(2) Selected (SD)	(3) Difference (SE)	(4) Excluded (SD)	(5) Selected (SD)	(6) Difference (SE)	(7) Difference (SE)	(8) PWR step	(9) Verif. Step
Total weekly income per capita (Lempiras)	74.98	50.59	24.40	46.74	51.35	−4.62	17.54	109 %	−9 %
	(98.65)	(66.09)	(5.39)	(55.79)	(67.96)	(9.82)	(4.75)		
Household has business	0.19	0.10	0.09	0.10	0.10	0.00	0.07	99 %	1 %
	(0.39)	(0.30)	(0.03)	(0.30)	(0.30)	(0.04)	(0.03)		
Panel D: Consumption, poverty and vulnerability									
Total weekly consumption per adult equivalent (Lempiras)	166.91	128.49	38.41	148.03	124.53	23.50	38.27	79 %	21 %
	(120.23)	(118.01)	(9.66)	(230.51)	(77.11)	(9.55)	(8.21)		
Household below $1.25 poverty line	0.33	0.47	−0.14	0.45	0.48	−0.03	−0.12	91 %	9 %
	(0.47)	(0.50)	(0.04)	(0.50)	(0.50)	(0.06)	(0.04)		
Total ppi score	36.37	32.08	4.30	33.64	31.77	1.87	4.01	84 %	16 %
	(11.67)	(9.86)	(0.98)	(10.30)	(9.75)	(1.35)	(0.85)		
Food security index	0.52	−0.02	0.54	0.39	−0.09	0.48	0.58	73 %	27 %
	(1.29)	(1.62)	(0.11)	(1.34)	(1.66)	(0.17)	(0.11)		
Number of observations	195	702		67	635				

1. The asset index is created using PCA on 35 binary asset variables indicating whether the household owns each given asset. 0.105 of the overall variation is explained by the first component.
2. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<14), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.313 of the overall variation is explained by the first component.
3. The food security index is created using PCA on 6 variables: Whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating and/or skipped/reduced meals, and how frequently this happened. 0.612 of the overall variation is explained by the first component.
Source: Authors' analysis based on own data collected.

Table 3. Selection at each stage of TUP targeting process - Peru

	PWR step			Verification step			Final selection	Contributions to final selection (%)	
	(1) Excluded (SD)	(2) Selected (SD)	(3) Difference (SE)	(4) Excluded (SD)	(5) Selected (SD)	(6) Difference (SE)	(7) Difference (SE)	(8) PWR step	(9) Verif. Step
Panel A: Demographics and education									
Female-headed household	0.06	0.13	−0.07	0.14	0.13	0.01	-0.06	103 %	−3 %
	(0.24)	(0.33)	(0.04)	(0.35)	(0.33)	(0.06)	(0.03)		
Years of education of household head	6.33	5.21	1.13	6.42	5.10	1.33	1.25	79 %	21 %
	(3.44)	(3.63)	(0.43)	(4.26)	(3.55)	(0.88)	(0.41)		
School enrollment (boys: 12-17 years)	0.98	0.95	0.03	0.94	0.95	−0.01	0.03	107 %	−7 %
	(0.14)	(0.14)	(0.02)	(0.24)	(0.22)	(0.06)	(0.02)		
School enrollment (girls: 12-17 years)	0.93	0.89	0.04	1.00	0.88	0.12	0.06	67 %	33 %
	(0.26)	(0.26)	(0.07)	(0.00)	(0.32)	(0.07)	(0.07)		
Panel B: Household assets									
Household has radio	0.98	0.95	0.03	0.91	0.95	−0.04	0.01	164 %	−64 %
	(0.15)	(0.22)	(0.01)	(0.29)	(0.21)	(0.05)	(0.01)		
Household has bicylce	0.68	0.48	0.21	0.42	0.48	−0.06	0.17	107 %	−7 %
	(0.47)	(0.50)	(0.06)	(0.50)	(0.50)	(0.11)	(0.05)		
Asset index	1.33	−0.15	1.49	0.64	−0.22	0.87	1.47	88 %	12 %
	(1.73)	(2.37)	(0.22)	(2.54)	(2.35)	(0.58)	(0.22)		
Latrine with water or septic tank	0.22	0.25	−0.03	0.18	0.26	−0.08	-0.04	60 %	40 %
	(0.42)	(0.43)	(0.05)	(0.38)	(0.44)	(0.08)	(0.05)		
Housing index	0.12	0.00	0.12	0.04	−0.01	0.04	0.11	92 %	8 %
	(0.94)	(1.13)	(0.13)	(0.96)	(1.14)	(0.21)	(0.12)		
Panel C: Productive assets and income									
Total cultivated land (m2)	8144	4134	4009.36	4091	4138	−47.51	3487.26	100 %	0 %
	(8730)	(5793)	(1149)	(3335)	(5966)	(759)	(1030)		
Number of cattle	4.98	2.98	2.00	3.55	2.93	0.62	1.89	94 %	6 %
	(2.62)	(1.52)	(0.25)	(1.81)	(1.48)	(0.41)	(0.23)		
Number of sheep/goats	15.69	15.26	0.43	10.77	15.55	−4.79	−0.29	−134 %	234 %
	(17.69)	(14.78)	(1.87)	(12.71)	(14.87)	(3.05)	(1.77)		

(Continued)

TABLE 3. *Continued*

	PWR step			Verification step			Final selection	Contributions to final selection (%)	
	(1) Excluded (SD)	(2) Selected (SD)	(3) Difference (SE)	(4) Excluded (SD)	(5) Selected (SD)	(6) Difference (SE)	(7) Difference (SE)	(8) PWR step	(9) Verif. Step
Total weekly income per capita (Lempiras)	10.00	5.63	4.37	7.36	5.48	1.88	4.19	91 %	9 %
	(22.58)	(8.02)	(2.44)	(12.04)	(7.56)	(2.42)	(2.16)		
Household has business	0.28	0.14	0.15	0.23	0.13	0.10	0.15	86 %	14 %
	(0.45)	(0.34)	(0.06)	(0.42)	(0.34)	(0.09)	(0.05)		
Panel D: Consumption, poverty and vulnerability									
Total weekly consumption per adult equivalent (Lempiras)	44.48	36.96	7.51	33.17	37.27	4.10	5.86	113 %	−13 %
	(25.85)	(21.24)	(2.91)	(19.79)	(21.34)	(4.00)	(2.71)		
Household below $1.25 poverty line	0.92	0.83	0.09	0.76	0.84	0.07	0.06	122 %	−22 %
	(0.27)	(0.37)	(0.05)	(0.43)	(0.37)	(0.10)	(0.05)		
Total ppi score	17.69	16.15	1.55	19.46	15.85	3.61	2.07	65 %	35 %
	(7.13)	(7.67)	(0.76)	(9.48)	(7.43)	(2.05)	(0.73)		
Food security index	−0.12	0.07	−0.19	0.01	0.07	−0.07	-0.18	93 %	7 %
	(1.68)	(1.57)	(0.22)	(1.46)	(1.57)	(0.28)	(0.20)		
Number of observations	154	563		27	536				

1. The asset index is created using PCA on 51 binary asset variables indicating whether the household owns each given asset. 0.115 of the overall variation is explained by the first component.
2. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<14), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.264 of the overall variation is explained by the first component.
3. The food security index is created using PCA on 6 variables: Whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating and/or skipped/reduced meals, and how frequently this happened. 0.522 of the overall variation is explained by the first component.
Source: Authors' analysis based on own data collected.

Honduras) reflect sorting into groups by higher and lower welfare. In both countries, indicators of education, household assets, productive assets, and consumption, poverty, and vulnerability reflect consistent sorting into groups by welfare status.

More statistically significant differences between selected and excluded households emerge in Honduras than in Peru. Notably, the PWR in Peru did not sort households by weekly income per capita or food security, although the lack of a significant difference for the former may stem from the challenge of measuring income. Reported income for both groups is much lower than consumption measures, reflecting this challenge.

Verification

Selection at the verification step (columns 4–6 of tables 2 and 3) shows fewer statistically significant differences relative to the PWR. Note however that the number of excluded households in this step is small, reducing our power to detect statistically significant differences. In Honduras, differences emerge in boys' enrollment, assets (the asset index, latrine ownership, the housing index, and land ownership), weekly consumption per adult equivalent, and food security, each reflecting sorting consistent with poverty status. In Peru, we find statistically significant differences in the expected direction only for girls' school enrollment and the PPI. The latter is not unexpected given that the PPI score was itself one of the criteria used in the verification step. Excluded households have fewer sheep and goats than the selected households. In Peru, sheep and goats are livestock typical of poorer households, with the richer households holding cattle, lamas and alpacas.

Given the fewer differences within the verification step relative to the PWR step, it appears that the verification step mostly served to identify and correctly exclude a few wealthier households, while the PWR effectively sorted households broadly into poor and wealthy categories.

Final Selection

Column 7 of tables 3 and 4 shows the results of the complete TUP targeting process with the final difference between households excluded in either the PWR or verification step and those selected in both of them. In both countries, the significant differences in the final selection echo those in the PWR. Taken as a whole, the selection process effectively targeted poorer households according to a wide range of indicators. As can be seen in columns 8–9, the PWR was responsible for the majority of the differences between the selected and excluded groups in both Honduras and Peru.[8]

8. The numbers in columns 8–9 indicate the relative contribution of the PWR and verification steps. Let M be the mean of the variable of interest, M1 its mean conditional on being selected in the PWR step and M2 the mean conditional on being finally selected, the contribution of the PWR is then defined as (M–M1)/(M–M2) and the contribution of the verification step as (M1–M2)/(M–M2).

TABLE 4. Mistargeting of different selection methods by consumption quintile - Honduras

Quintile of per capita consumption distribution	(1) Random selection (%)	(2) Perfect targeting (%)	(3) Complete TUP targeting (%)	(4) Housing Index targeting (%)	(5) PPI targeting (%)	(6) p-value (1) = (3)	(7) p-value (1) = (4)	(8) p-value (1) = (5)	(9) p-value (3) = (4)	(10) p-value (3) = (5)	(11) p-value (4) = (5)	(12) Number of obs.
1st quintile	52 %	100 %	56 %	68 %	64 %	0.32	0.00	0.00	0.02	0.14	0.34	188
2nd quintile	52 %	100 %	61 %	61 %	64 %	0.05	0.04	0.00	0.97	0.62	0.51	187
3rd quintile	52 %	60 %	60 %	55 %	56 %	0.05	0.46	0.28	0.30	0.45	0.72	189
4th quintile	52 %	0 %	47 %	47 %	46 %	0.25	0.21	0.15	0.92	0.81	0.88	169
5th quintile	52 %	0 %	35 %	29 %	29 %	0.00	0.00	0.00	0.12	0.17	0.92	147

1. This table compares the complete TUP selection process to alternative targeting procedures: a housing index and the PPI score. Households were ranked according to per capita consumption (adult equivalence: 1 = adult; 0.5 = child<14) and for each quintile of the consumption distribution, we calculate the % of households that were (or would have been) selected by each of the methods. Since the complete selection process identified the poorest 52% and not a complete ranking, the housing index and PPI methods mimick that selection, i.e. a household is selected if it ranks among the 52% lowest scoring households.
2. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<14), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.313 of the overall variation is explained by the first component.
3. The number of observations is based on the analysis sample, with households misisng data on either per capita consumption, PPI or the housing index getting dropped.
Source: Authors' analysis based on own data collected.

IV. TUP Targeting in Comparison to Other Targeting Methods

The mean comparisons examined above indicate that the TUP selection process broadly sorted households by welfare status. Such sorting is an important, but not sufficient indication of how well the process identifies poor households: the process may have erred more towards false positives, or false negatives, which may have important welfare consequences, and the process may have worked well but not as well as other methods (or worked equally as well but cost more). We use a well-established measure of poverty, consumption per capita, as well as an asset index as benchmarks to compare the TUP targeting process with random selection and two PMTs: the PPI and a housing index.

Consumption per Capita as a Bnchmark

We choose consumption per capita as a benchmark assuming that it represents the best available proxy for well-being. We use an equivalence of 1 for adults and 0.5 for children under the age of 14. Caution is needed, however, for several reasons. First, the measurement of consumption for poor households is inherently difficult. Respondents do not always remember their expenditures accurately, do not tend to measure the consumption of their own produce in standardized units, and may perceive an incentive to inflate or deflate their reported expenditure. Second, survey-based measurement of consumption usually refers to a short time period; for some households, those time periods may not be representative of their typical consumption habits. Third, households have different consumption preferences: a household that chooses to spend as little as possible and save for the future may appear poorer than it actually is when consumption is used as the benchmark. Fourth and finally, consumption does not capture other dimensions of poverty, such as vulnerability to shocks or social and political inclusion. In sum, while we consider consumption to be the best benchmark available to compare targeting tools, we interpret the results with caution.

Asset Index as a Benchmark

We also use an asset index as a benchmark to compare the TUP targeting process and two PMTs. An asset index has strengths and weaknesses. In comparison to expenditures, it is typically more stable, that is, less short-term fluctuation. Furthermore, some assets can be verified by the surveyor (while others naturally are at risk of self-reporting bias, just as expenditures are). A weakness is that assets are driven by savings preferences (both in levels and types) as well as life cycle status. Regardless, we also will include a comparison to an asset index to benchmark the poverty proxies and examine whether certain proxies are more correlated with assets (vs expenditures, the primary benchmark).

Other Targeting Methods

We compare the TUP selection process with two proxy means tests: the PPI and a housing index. The PPI is a poverty scorecard that estimates the likelihood that a household is poor based on ten questions related to demographics, education, housing, and assets. The information takes about five minutes to collect and many of the answers are readily verifiable if the questionnaire is performed in the home. Answers to each question correspond to a certain number of points; the sum of these points yields a score out of 100 for the overall survey. Each score is then associated via a scorecard with a probability that the household falls below the poverty line, which is a per capita cutoff. Thus, the PPI is calibrated to replicate a per capita poverty measure and can be reasonably compared to our per capita poverty measures. The scorecard is calibrated using data from the relevant country's national household survey. The choice and weighting of indicators is based on their correlation with poverty, the ease of collecting and verifying the information, and the liability of the indicator to change over time as poverty status changes (Schreiner 2009, 2010).

We constructed a housing index using principal components analysis (PCA), a statistical technique often used in the creation of socio-economic status indices from household survey data. Five variables were entered into the PCA: the total number of rooms in the house per adult equivalent (1 for adult, 0.5 for children under 14) and dummy variables indicating whether the house has a cement floor, a cement wall, a latrine, and electricity access. From this set of correlated variables, PCA creates uncorrelated components that explain the variance in the data and thus provide synthesized information on the underlying concept—in this case, housing quality. The components are ordered so that the first component explains the largest amount of variation in the data (Vyas and Kumaranayake 2006). This first principal component is then used as a relative index of housing quality, which we use as a proxy for overall well-being.

The housing index contains four binary household level variables and one per capita measure (no. of rooms). There is some critique within statistical literature of using PCA on binary variables; however, it is a common practice within empirical literature to create wealth indices using asset indicators (see Filmer and Pritchett 2001). PCA using discrete variables is the approach also used by the Demographics and Health Surveys (DHS) program to create the DHS Wealth Index ("Wealth Index" 2015).

Results

Our approach evaluates how well the various targeting methods categorize households at various quintiles in the distribution of the two different benchmarks: consumption per capita and an asset index. We compare the TUP targeting method against a naive random selection, the PPI, and the housing index. For the PPI and housing index, we choose the poverty line—that is, the cut-off value to be categorized as poor— in each country so that the bottom X% of households get selected where X is the percentage of households selected by the actual TUP targeting process (52% for Honduras and 59% for Peru). For each quintile of a given benchmark, we then calculate the fraction of households in that quintile that would be selected by a given targeting method. A perfect targeting tool would select all households in percentiles of the benchmark less than X% and not select any households in percentiles above X%. A naively random sampling would achieve a rate of X% for each quintile.

Table 4 (Honduras) and table 5 (Peru) show the results of the comparisons using consumption per capita as a benchmark, while table 6 (Honduras) and table 7 (Peru) show the results using the asset index as a benchmark. Columns 1, 2, 3, 4, and 5 show the fraction of households within a particular quintile of the benchmark that would be selected by the given targeting tool. As column 2 shows, perfect targeting would select 100% of respondents in all percentiles before the cutoff point for selection (52% in Honduras and 59% in Peru), and 0% afterward. The other columns present the *p*-values from tests of equality of proportions selected between two of the targeting tools. With some exceptions—particularly in Honduras—both tables show few consistent differences in performance among the targeting tools and between each targeting tool and a mere random selection.

Consumption per Capita Results

As table 4 shows for Honduras, there is some evidence for differences between each targeting tool and a random sample but very little evidence for differences among targeting tools. Each targeting tool significantly outperforms the random sample in at least three quintiles, concentrated in one or both tails. Between targeting tools, the only significant difference we observe is in the bottom quintile when comparing the TUP process with the housing index, with housing outperforming the TUP process.

In table 5 for Peru, only the first and fifth quintiles of the housing index and PPI show significant differences from mere random selection. The TUP process does not perform differently than random selection in any quintile. Of the fifteen tests (3 methods $\times$ 5 quintiles) performed that compare targeting tools to each other, not one shows a statistically significant difference.

Figures 1 and 3 visually depict the performance of each targeting tool using consumption per capita as a benchmark.[9] An ideal targeting tool would have a straight line from the point (0,1) to (X,1), followed by a straight line from (X,0) to (1,0), where X corresponds to the percentage of households finally selected in each country. Even though each targeting tool displays a downward sloping trend, none comes close to the ideal values. In both graphs, there is evidence that the tools perform relatively well at the tails, with the sharpest changes in slope occurring at the very left and right ends of the graphs. The shape implies that the

9. The graphs depict fractions of nonparametrically estimated density functions. Because of the nonparametric smoothing, they do no perfectly map into the fractions in tables 3 and 4.

TABLE 5. Mistargeting of different selection methods by consumption quintile - Peru

Quintile of per capita consumption distribution	(1) Random selection (%)	(2) Perfect targeting (%)	(3) Complete TUP targeting (%)	(4) Housing Index targeting (%)	(5) PPI targeting (%)	(6) p-value (1) = (3)	(7) p-value (1) = (4)	(8) p-value (1) = (5)	(9) p-value (3) = (4)	(10) p-value (3) = (5)	(11) p-value (4) = (5)	(12) Number of obs.
1st quintile	59 %	100 %	67 %	72 %	74 %	0.23	0.05	0.02	0.44	0.21	0.49	123
2nd quintile	59 %	100 %	64 %	63 %	56 %	0.39	0.39	0.59	0.91	0.12	0.38	147
3rd quintile	59 %	95 %	53 %	62 %	54 %	0.32	0.62	0.44	0.36	0.84	0.43	127
4th quintile	59 %	0 %	61 %	53 %	60 %	0.79	0.31	0.88	0.25	0.93	0.41	140
5th quintile	59 %	0 %	50 %	45 %	47 %	0.13	0.01	0.04	0.42	0.71	0.80	129

1. This table compares the complete TUP selection process to alternative targeting procedures: a housing index and the PPI score. Households were ranked according to per capita consumption (adult equivalence: 1 = adult; 0.5 = child<14) and for each decile of the consumption distribution, we calculate the % of households that were (or would have been) selected by each of the methods. Since the complete selection process identified the poorest 59% and not a complete ranking, the housing index and PPI methods mimick that selection, i.e. a household is selected if it ranks among the 59% lowest scoring households.
2. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<14), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.264 of the overall variation is explained by the first component.
3. The number of observations is based on the analysis sample, with households misisng data on either per capita consumotion, PPI or the housing index getting dropped.
Source: Authors' analysis based on own data collected.

Table 6. Mistargeting of different selection methods by asset index quintile - Honduras

Quintile of asset index distribution	(1) Random selection (%)	(2) Perfect targeting (%)	(3) Complete TUP targeting (%)	(4) Housing Index targeting (%)	(5) PPI targeting (%)	(6) p-value (1) = (3)	(7) p-value (1) = (4)	(8) p-value (1) = (5)	(9) p-value (3) = (4)	(10) p-value (3) = (5)	(11) p-value (4) = (5)	(12) Number of obs.
1st quintile	52 %	100 %	69 %	71 %	60 %	0.00	0.00	0.03	0.70	0.10	0.01	203
2nd quintile	52 %	100 %	71 %	69 %	62 %	0.00	0.00	0.01	0.78	0.11	0.08	201
3rd quintile	52 %	60 %	54 %	53 %	54 %	0.58	0.86	0.64	0.74	0.94	0.78	176
4th quintile	52 %	0 %	45 %	46 %	51 %	0.07	0.14	0.72	0.83	0.30	0.38	173
5th quintile	52 %	0 %	21 %	21 %	33 %	0.00	0.00	0.00	1.00	0.01	0.01	131

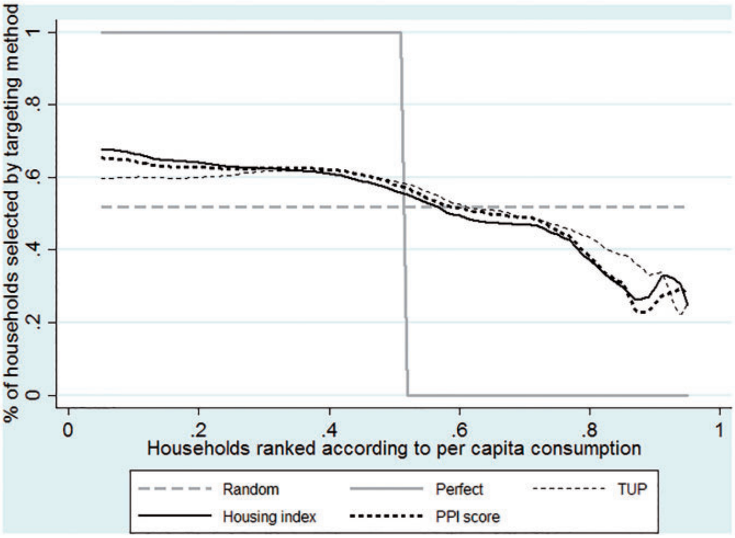
1. This table compares the complete TUP selection process to alternative targeting procedures: a housing index and the PPI score. Households were ranked according to an asset index and for each quintile of the asset index distribution, we calculate the % of households that were (or would have been) selected by each of the methods. Since the complete selection process identified the poorest 52% and not a complete ranking, the housing index and PPI methods mimick that selection, i.e. a household is selected if it ranks among the 52% lowest scoring households.
2. The asset index is created using PCA on 35 binary asset variables indicating whether the household owns each given asset. 0.105 of the overall variation is explained by the first component.
3. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<14), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.313 of the overall variation is explained by the first component.
4. The number of observations is based on the analysis sample, with households misisng data on either per capita consumotion, PPI or the housing index getting dropped.
Source: Authors' analysis based on own data collected.

TABLE 7. Mistargeting of different selection methods by asset index quintile - Peru

Quintile of asset index distribution	(1) Random selection (%)	(2) Perfect targeting (%)	(3) Complete TUP targeting (%)	(4) Housing Index targeting (%)	(5) PPI targeting (%)	(6) p-value (1) = (3)	(7) p-value (1) = (4)	(8) p-value (1) = (5)	(9) p-value (3) = (4)	(10) p-value (3) = (5)	(11) p-value (4) = (5)	(12) Number of obs.
1st quintile	59 %	100 %	83 %	78 %	65 %	0.00	0.00	0.26	0.30	0.00	0.00	144
2nd quintile	59 %	100 %	66 %	63 %	66 %	0.22	0.39	0.18	0.69	0.99	0.56	147
3rd quintile	59 %	95 %	58 %	54 %	58 %	0.90	0.46	0.86	0.74	0.98	0.67	142
4th quintile	59 %	0 %	47 %	50 %	72 %	0.06	0.17	0.01	0.68	0.01	0.01	125
5th quintile	59 %	0 %	39 %	46 %	33 %	0.00	0.03	0.00	0.44	0.37	0.12	124

1. This table compares the complete TUP selection process to alternative targeting procedures: a housing index and the PPI score. Households were ranked according to their score in an asset index and for each decile of the asset index distribution, we calculate the % of households that were (or would have been) selected by each of the methods. Since the complete selection process identified the poorest 59% and not a complete ranking, the housing index and PPI methods mimick that selection, i.e. a household is selected if it ranks among the 59% lowest scoring households.
2. The asset index is created using PCA on 51 binary asset variables indicating whether the household owns each given asset. 0.115 of the overall variation is explained by the first component.
3. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence ($1 = \text{adult}$; $0.5 = \text{child} < 14$), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.264 of the overall variation is explained by the first component.
4. The number of observations is based on the analysis sample, with households misisng data on either per capita consumotion, PPI or the housing index getting dropped.
Source: Authors' analysis based on own data collected.

Figure 1. Comparing TUP to consumption per capita—Honduras



Source: Authors' analysis based on own data collected.

targeting tools are better at identifying the very poorest and the very richest than they are at correctly categorizing individuals in the middle.

In both graphs, no tool consistently outperforms the others. The PPI in Peru, for instance, outperforms the TUP process and housing index in including the very poorest, but in the rest of the distribution has mixed performance. The housing index in Honduras also starts out well beginning in the left tail and through the ninth decile rivals the other tools but then rises for the last decile, including a higher proportion of wealthy households.

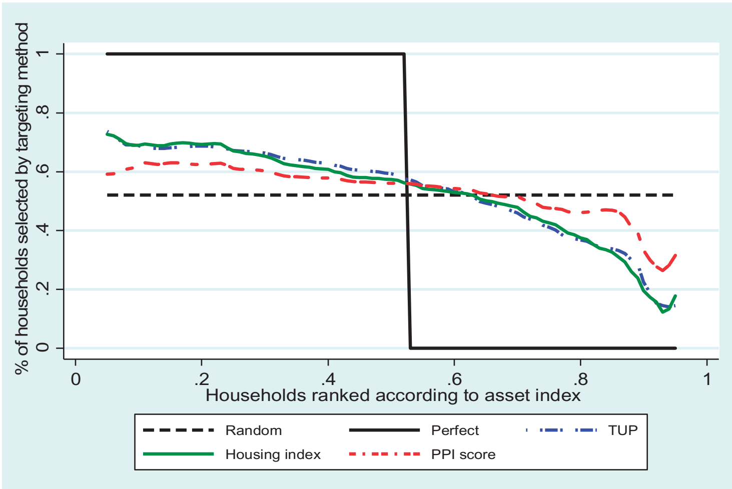
Taken together, the figures and tables paint a mixed picture: the targeting tools each perform slightly (albeit often weakly, statistically) better than random selection—particularly in the tails and in Honduras. But the targeting tools compared to each other show few consistent differentiating patterns.

Asset Index Results

Table 6 (Honduras) and table 7 (Peru) show the results of the comparisons using the asset index, rather than the above consumption per capita measure, as the benchmark "truth."

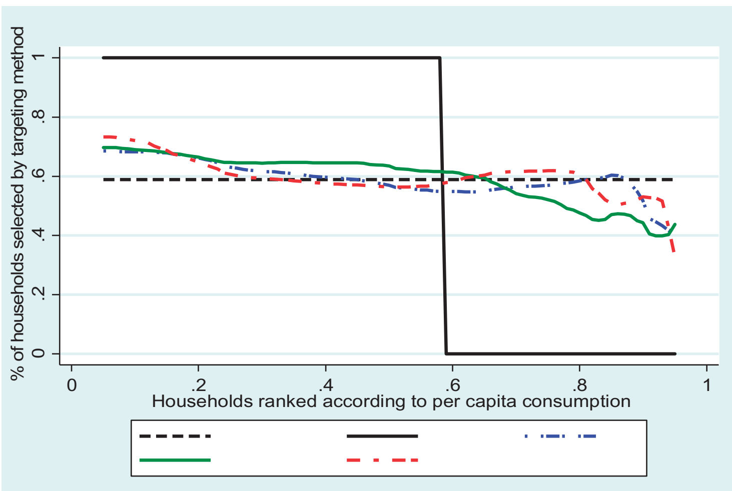
We see results in Honduras similar to those when using the consumption benchmark, with significant differences between all three targeting methods and random selection in at least three quintiles. The TUP targeting process is the strongest, outperforming random selection in four of the five quintiles. In comparing the targeting methods to one another, TUP targeting and the housing index perform similarly, with no quintiles differing between the two. However, when compared to PPI, they both perform better. TUP outperforms PPI in two quintiles, while the housing index outperforms PPI in four quintiles.

FIGURE 2. Comparing TUP to an asset index – Honduras



Source: Authors' analysis based on own data collected.

FIGURE 3. Comparing TUP to consumption per capita – Peru

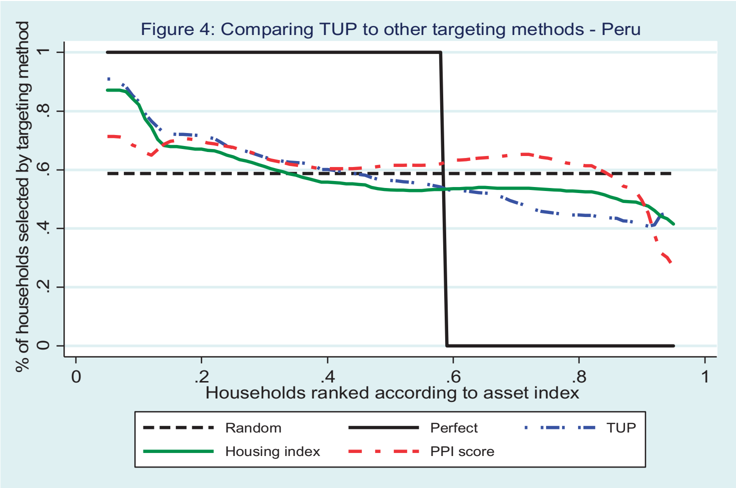


Source: Authors' analysis based on own data collected.

In Peru, TUP targeting also performs the best, with three quintiles performing better than random selection, concentrated in the tails. The housing index and PPI do better in two quintiles. Similar to in Honduras, TUP and the housing index do not differ from one another in any quintile, while they both outperform the PPI in two quintiles.

The figures illustrate the same patterns seen in the tables. In figure 2, for Honduras, all three methods appear slightly better than random selection, particularly in the tails. The graph shows PPI doing consistently poorer than the

FIGURE 4. Comparing TUP to an asset index – Peru



Source: Authors' analysis based on own data collected.

housing index and TUP process, with the two latter performing similarly throughout the distribution.

In figure 4, we once again see PPI getting outperformed by the housing index and TUP process for the majority of the distribution. For a portion of the distribution, PPI appears worse than random selection. All three outperform random selection in the tails. The housing index and TUP process are visually comparable, and both outperform random selection for the majority of the distribution.

V. OTHER DEFINITIONS OF POVERTY

For the reasons outlined in section 4, we present our results using consumption per capita and an asset index as "the" measures of poverty with some caution. Moreover, even if these are the strongest proxies for poverty, given measurement error, other measures may shed light on the relative performance of targeting tools. Tables A1 and A2 thus extend the comparison of TUP with other targeting tools by examining each tool's performance using additional benchmarks for poverty. Each cell shows among households selected by the targeting method in the column heading the percentage of households that rank in the bottom X% (52% in Honduras and 59% in Peru) according to the poverty metric on the left. As before, we compare the targeting tools to random selection, which would select X% of households in the bottom X% of the poverty distribution for each metric. A perfect targeting tool would only select those bottom X%; hence, the number selected for each metric is 100%.

In the first row of the tables we show how each tool fares on average for consumption per capita. Among random selection, TUP, the housing index, and PPI in Peru, only the housing index does better than random selection and it also outperforms TUP targeting. In Honduras, all targeting tools perform better than random selection, but once again the housing index does better than TUP targeting.

Clearer differences emerge among the tools when using the total value of animals and total cultivated land as benchmarks. For total value of animals, the relative ranking for the three tools is the same in each country. For Honduras and Peru, respectively, the percent correctly identified as poor, using total value of animals, is TUP (66% and 72%) > Housing (62% and 58%) > PPI (57% and 57%) > random (52% and 59%). TUP's performance is statistically significantly better than the other two methods in both countries. Similarly, for total cultivated land as the "true" measure of poverty, TUP outperforms both PPI and Housing. These results suggest that for total value of livestock and total value of cultivated land, TUP generally outperforms random selection and both the housing index and PPI.

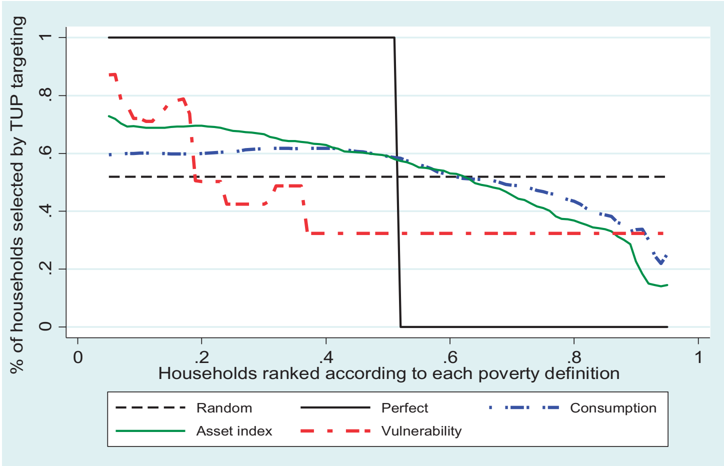
Few consistent differences among the tools appear when vulnerability to reductions in food consumption[10] and years of education of the household head are each used as the true measure of poverty. In Honduras, each of the tools is significantly better than random selection for both metrics but no method outperforms another. In Peru, the only tool to outperform random selection for the two metrics is PPI for years of education of the household head. PPI also outperforms TUP targeting for years of education of the household head.

Figures 5 and 6 capture TUP's performance visually. The graphs plot the percentage of households selected by the TUP targeting process against the rank of those households according to three metrics of poverty: the asset index, consumption, and vulnerability to reductions in food consumption. TUP performs best according to the asset index in Peru and Honduras, showing a consistent negative slope from including poor households on the left to excluding rich households on the right. A similar, but weaker, trend exists for consumption. The TUP process shows an inverse relationship between vulnerability and selection in Peru and a direct, but weak relationship in Honduras.

Overall, the comparison unveils three insights into the TUP selection process. First, when judged using five different poverty metrics, the TUP process typically performs better than random selection. Second, the TUP process, compared to PPI and the Housing index, leads to selecting households with less land and less valuable livestock. Third, the pattern demonstrates that the TUP process performs best for measures that are easily observable to the community, that is, the TUP process leads to selection on assets and less so on consumption or education.

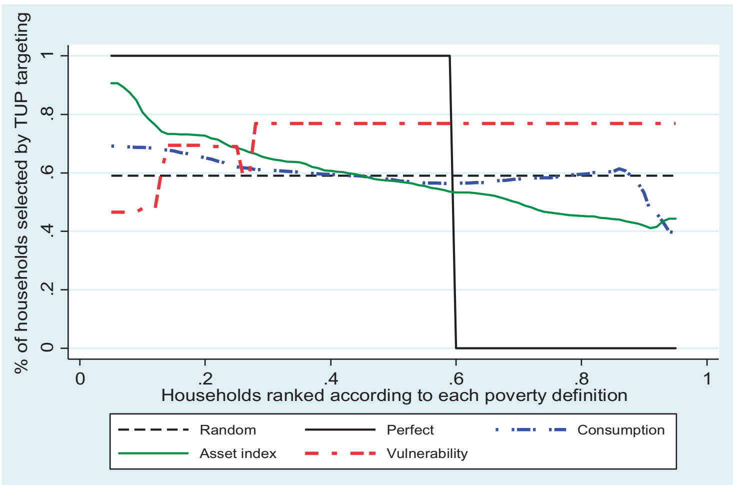
10. As a measure of vulnerability to reductions in food consumption, we use an index based on questions in the survey about whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating and/or skipped/reduced meals, and how frequently this happened.

Figure 5. Comparing poverty definitions – Honduras



Source: Authors' analysis based on own data collected.

Figure 6. Comparing poverty definitions – Peru



Source: Authors' analysis based on own data collected.

VI. Understanding PWR Rankings

TUP's favorable performance along some poverty indicators, but not others, makes poignant the question of what observable information predicts how village members categorize households. Tables A3 and A4 analyze these criteria by regressing a household's group number (ranking) in the PWR on a host of covariates. Column 1 shows the results of this regression, while column 2 displays results from the same regression with different outcome variables selection by the complete TUP process as the outcome variable.

With the five poverty metrics and other covariates included in one regression, the PWR process shows that households with a lower score on the asset index in Honduras and Peru and households with less livestock and land in Peru are more likely to be ranked as poor, while there is no difference in the rankings among households according to their vulnerability to reductions in food consumption which is consistent with earlier results. Interestingly, once controlling for other factors, the result in Peru on the asset index is inconsistent with our findings when comparing TUP targeting to random selection by asset index quintiles. Additional covariates are statistically significant in both countries, indicating that, conditional on the poverty metrics, villagers take into account other characteristics when ranking households. In Honduras, household size and having savings make a household less likely to be categorized as poor, whereas the household head being a widower has the opposite effect. In Peru, households selected by the PWR have a lower mean self-reported economic status while households with heads under 30 are more likely to be categorized as poor. Oddly, once controlling for all variables, higher consumption is actually positively correlated with being identified as poorer.

VII. Policy Implications and Conclusion

The relative costs and merits of each method hold important implications for organizations seeking to target the poor effectively. Past quantitative evaluations of PWR results using household surveys generally show that PWRs effectively identify households that are poor according to traditional measures of wealth. Here we help build evidence across two sites, Honduras and Peru. We find strikingly similar results, although implemented in different geographies, cultures and implementing organizations. Naturally, this does not imply the results are a universally true, but the two site analysis does help explore the bounds of external validity more so than one can do with a one site analysis as is common in this literature. Adams et al. (1997) uses expenditure, income, and asset holdings to validate a PWR in rural Bangladesh and find significant differences between wealth groups across all traditional socio-economic variables. Ojiako et al. (2009) and Temu and Due (2000) similarly find that PWRs in Nigeria and Tanzania, respectively, successfully identify poorer households. Van Campenhout (2007) studies a wealth ranking in rural Tanzania and finds that the wealth categories reflect asset holdings and schooling levels.[11]

While the results of PWRs against socioeconomic indicators are intrinsically interesting in terms of what we can learn about perceptions of poverty, their

11. Data were not available to compare the results with household income or expenditure.

performance relative to other targeting methods is directly relevant for policy. The relatively few studies that have made such comparisons have yielded mixed results. In a study in rural South Africa, Hargreaves et al. (2007) compare the results of a PWR with two survey-based methodologies that employ principal component analyses (PCA) to construct wealth indices. The PWR results are only weakly correlated with the survey-based tools, implying that one or the other (or both) is incorrect; however, in the absence of a credible benchmark it is impossible to determine which is more effective. Banerjee et al. (2009) evaluates a two-step targeting process used by Bandhan in India to establish eligibility for the same Graduation Program that is discussed in this paper. Using detailed household survey data to analyze the process, they find that the PWR approach compares favorably to the census-based methods used by the Indian government, although it is important to note that the latter fared particularly poorly.

Our study assesses a PWR targeting method relative to other common targeting methods, benchmarking all of the methods against traditional measures of wealth. Additionally, we employ a mixed method, using both a PWR and a verification step after geographic targeting, which is a strategy often used by governments. For example, Indonesia's Data Collection on Social Protection Programme (PPLS) determines its list of households that go on to receive a PMT survey using community methods (Alatas et al. 2012). By comparing the same methods against the same benchmarks in different settings, we improve the understanding of how PWRs work against different standards.

The data from our surveys of households selected and excluded by the TUP targeting process support the effectiveness of PWRs in sorting households by poverty status. The subsequent step in the TUP targeting process—the verification step—produced fewer and smaller differences between selected and excluded households but seems to have filtered some wealthy households out of the group selected in the PWR step. After benchmarking the TUP method against the distribution of consumption per capita and an asset index, the TUP process fares moderately but is mostly indistinguishable from two alternative targeting methods based on PMTs, the housing index and PPI. Differences that do emerge surface within the tails of the consumption expenditure and asset index distributions.

This raises the question of why, given that households in these close-knit communities are likely to know each other very well, the PWR is not more accurate. One explanation finds support in our analysis that uses alternative poverty metrics: when compared against land and livestock ownership, both the TUP process and PPI method outperform random selection and the housing index. This demonstrates that local definitions of poverty incorporate variables other than consumption and assets or are simply based on what is more readily available and observable to each other about each other. Results from a multivariate regression controlling for consumption and the asset index also reinforce this point, as livestock ownership predicts the rank in the PWR in both countries along with a number of other covariates that were unique to each country. Noticeably absent from the list of predictors of the PWR ranking is vulnerability to reductions in food consumption.

Due to PWR's use of direct community involvement, it is perhaps unsurprising we see changes in variables that may be more incorporated in local definitions of poverty than consumption or asset ownership. A possible benefit of incorporating local interpretations of poverty is increased satisfaction with the targeting process, making the program easier to run. A field experiment conducted in Indonesia comparing a PMT and PWR (Alatas et al. 2012) found that while the PMT was more accurate when poverty was defined in terms of consumption, the villagers themselves were more satisfied with the results of the PWR. They also found fewer complaints when distributing the program in the treatment villages that used PWR compared to the PMT. They provide suggestive evidence that this difference is not due to the difference in lists produced by the two methods but rather due to the differing perceptions of the methods. Transparency and villagers' involvement in the process regardless of the outcome are also likely to increase satisfaction with the targeting process. Overall, these characteristics of PWRs and the resulting satisfaction of villagers may ease the implementation of targeted programs that can otherwise be controversial processes.

Despite the beneficial properties of PWRs, a primary concern that still exists is that of elite capture, where local leaders or elites manipulate the targeting process or distribution of a program to benefit themselves. Bardhan and Mookherjee (2000) shows that the threat of elite capture is dependent upon a number of diverse factors, thus a greater understanding of one's particular setting is needed to mitigate the risk. They argue that income inequality is one of these factors under which local capture is more likely to occur. It is important to consider different forms of inequality, socially and economically, that may increase the risk of elite capture in a community. We do not have sufficient variation in inequality and social and political structure in our setting to examine these issues, and thus it would be a mistake to extrapolate from our study to argue that elite capture is not an issue in other settings. The one-off nature of our process may also lead to an underestimate of the propensity for elite capture. For example, after learning more about the program and its processes, local leaders in Colombia started manipulating the targeting system of a transfer program (Camacho and Conover 2011). Elite capture also can happen in the actual distribution and implementation of a program, not merely in the identification of official participants (see Alatas et al. 2013).

Ultimately, the decision on what mechanism to use to target should be driven by a cost-benefit analysis. Table 8 provides an analysis of the estimated cost of each of the methods, in both countries. Our calculated costs for each method are based on estimates of facilitator and data entry assistant wages, transport costs, and survey material costs. Respondents' time was not considered in the calculation. The TUP targeting process (both the participatory wealth ranking and the verification step) costs about US$7 per selected household, whereas the PPI or housing index would cost about US$5.5 per selected household. We include a

Table 8. Estimated costs of targeting for Peru and Honduras

	Peru			Honduras		
	Total ($)	Per hh screened ($)	Per hh selected ($)	Total ($)	Per hh screened ($)	Per hh selected ($)
Two step targeting	33,127	3.85	7.41	26,272	3.30	6.34
PWR	16,340	1.90	3.65	13,333	1.67	3.21
Verification	16,787	1.95	3.75	13,038	1.63	3.13
PPI/Housing Index	26,230	3.05	5.87	20,967	2.62	5.04
Random Selection	0	0.00	0.00	0	0.00	0.00

Source: Authors' analysis based on own data collected.

cost of $0 for random selection to provide a reminder of these costs over simple random selection after geographic targeting. The approaches beyond random selection have quite similar costs, but the TUP targeting process is the most expense. That cost is divided almost equally, half coming from the PWR and half from the verification step.[12] Thus if the verification step was deemed unnecessary (and our evidence suggests it contributed little to the poverty targeting), the PWR method would be substantially cheaper than the PPI or housing index methods which require household visits.[13]

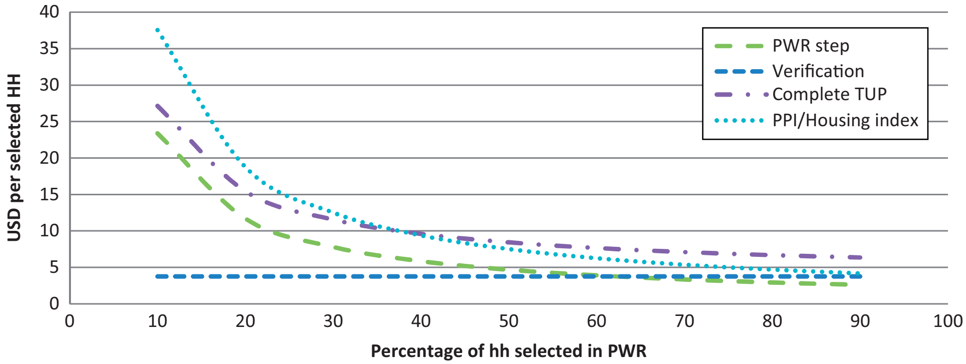
Of course, the relative costs of the different targeting methods are a function of context-specific parameters, such as the average number of households in a community and the percentage of targeted households. We consider those here in figures 7 and 8, by plotting the (hypothetical) targeting cost per selected household as a function of these parameters for the Peruvian case – fixing the other parameters at their observed values. As seen in figure 7, the PWR is substantially cheaper than the PPI/housing index independent of the percentage of households that is targeted (for an observed average village size of slightly under 100 households). Figure 8 shows however that this relationship does not hold for small villages (less than 60 households) where the PPI/housing index is cheaper than the PWR. As village size increases, the PWR becomes cheaper relative to the PPI/housing index because the marginal cost of ranking one more household in the PWR is close to zero.

On the benefit side, the benefits of one approach versus another depend critically on the social welfare function one is maximizing, and implicitly from that, what the lost benefits are from resources "wasted" on delivering services to untargeted individuals. For instance, someone who is barely above the bar (thus

12. The PPI/housing index and the verification step both make use of short household surveys. The cost of the verification survey is lower than the PPI/housing index survey because the verification survey includes only households selected in the PWR step.

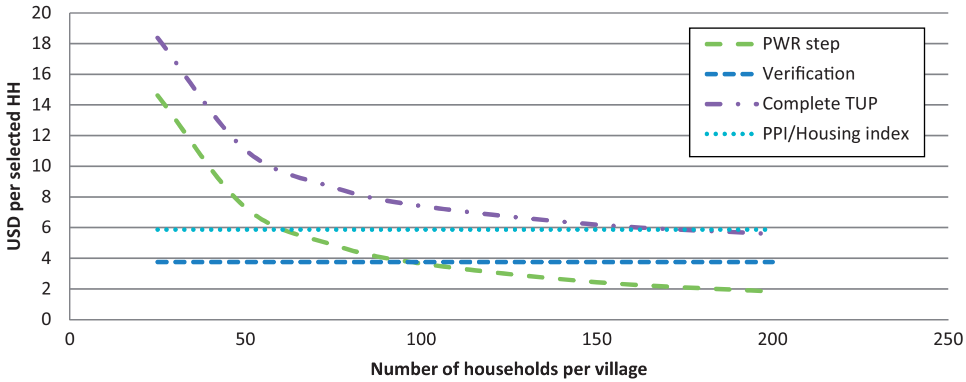
13. Our analysis focused on the poverty dimension of the targeting process and showed that the verification step contributed little to the poverty targeting. As mentioned above, the verification step also served a second objective, to verify a household's programmatic eligibility. If the verification step were deemed unnecessary, the screening of the programmatic criteria could be made part of the PWR process.

FIGURE 7. Cost per selected household as a function of % of HHs selected in PWR (Peru)



Source: Authors' analysis based on own data collected.

FIGURE 8. Cost per selected household as a function of village size (Peru)



Source: Authors' analysis based on own data collected.

not "ultra-poor" in a binary sense) still would benefit from the program and serve the greater social purpose of the program, just not as much as the person categorized as ultra-poor. Additionally, the benefit of community methods versus PMTs can depend on whether one wants to specifically target a hard measure of poverty (e.g., income) or a soft one (e.g., perceptions) (Alatas et al. 2012). Our results suggesting PWRs incorporate more local perceptions of poverty and more easily observable proxies (i.e., assets rather than consumption) echo the need for this consideration. Lastly, for programs that require some level of community engagement, PWRs may have the added benefit of increasing buy-in from community members, thus increasing the effectiveness of the program itself (for reasons similar to those observed in Alatas et al. 2012). This is not viable to examine in this project, as there were no communities that did not receive the PWR but is an area worthy of further research.

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Appendix

Table A1. Poverty rates among targeted households using different poverty metrics - Honduras

Poverty metric	(1) Random selection (%)	(2) Perfect targeting (%)	(3) Complete TUP targeting (%)	(4) Housing Index targeting (%)	(5) PPI targeting (%)	(6) p-value (1) = (3)	(7) p-value (1) = (4)	(8) p-value (1) = (5)	(9) p-value (3) = (4)	(10) p-value (3) = (5)	(11) p-value (4) = (5)
Total weekly consumption per adult equivalent	52 %	100 %	59 %	63 %	62 %	0.00	0.00	0.00	0.05	0.16	0.70
Vulnerability to reductions in food consumption	52 %	100 %	60 %	60 %	59 %	0.00	0.00	0.01	0.83	0.72	0.53
Total value of livestock owned	52 %	100 %	66 %	62 %	57 %	0.00	0.00	0.06	0.03	0.00	0.01
Total cultivated land	52 %	100 %	61 %	57 %	53 %	0.00	0.05	0.64	0.03	0.00	0.07
Education level of household head	52 %	100 %	60 %	60 %	58 %	0.00	0.00	0.01	0.82	0.48	0.55

1. This table shows poverty rates among targeted households for each of the targeting methods (column) using different poverty metrics (row). Since the complete selection process identified the poorest 52%, a household is considered poor according to each of the metrics if it ranks among the 52% lowest scoring households on the metric.
2. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<14), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.313 of the overall variation is explained by the first component.
3. The vulnerability to reductions in food indicator is an index created using PCA on 6 variables: Whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating and/or skipped/reduced meals, and how frequently this happened. 0.612 of the overall variation is explained by the first component.

Source: Authors' analysis based on own data collected.

TABLE A2. Poverty rates among targeted households using different poverty metrics - Peru

Poverty metric	(1) Random selection (%)	(2) Perfect targeting (%)	(3) Complete TUP targeting (%)	(4) Housing Index targeting (%)	(5) PPI targeting (%)	(6) p-value (1) = (3)	(7) p-value (1) = (4)	(8) p-value (1) = (5)	(9) p-value (3) = (4)	(10) p-value (3) = (5)	(11) p-value (4) = (5)
Weekly consumption per adult equivalent	59 %	100 %	61 %	66 %	62 %	0.46	0.03	0.34	0.07	0.65	0.24
Vulnerability to reductions in food consumption	59 %	100 %	58 %	61 %	58 %	0.71	0.68	0.81	0.32	0.92	0.39
Total value of livestock owned	59 %	100 %	72 %	58 %	57 %	0.00	0.80	0.52	0.00	0.00	0.66
Total cultivated land	59 %	100 %	66 %	59 %	59 %	0.00	0.97	0.92	0.02	0.01	0.88
Education level of household head	59 %	100 %	63 %	60 %	67 %	0.19	0.81	0.01	0.40	0.09	0.02

1. This table shows poverty rates among targeted households for each of the targeting methods (column) using different poverty metrics (row). Since the complete selection process identified the poorest 59%, a household is considered poor according to each of the metrics if it ranks among the 59% lowest scoring households on the metric.
2. The housing index is created using PCA on 5 variables: number of rooms per adult equivalence (1 = adult; 0.5 = child<15), and whether the house has a cement floor, a cement wall, a latrin, and electricity. 0.264 of the overall variation is explained by the first component.
3. The vulnerability to reductions in food indicator is an index created using PCA on 6 variables: Whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating, and how frequently this happened. 0.522 of the overall variation is explained by the first component.
Source: Authors' analysis based on own data collected.

TABLE A3. Regressions - Honduras

	(1) Group number in PWR (higher = poorer)	(2) Complete TUP targeting (1=poorest, 0=not poorest)
Poverty metrics		
Total weekly consumption per adult equivalent (L 100)	−0.04	−0.03*
	(0.03)	(0.01)
Asset index	−0.16***	−0.05***
	(0.02)	(0.01)
Vulnerability to reductions in food consumption	0.00	0.02*
	(0.02)	(0.01)
Total value of livestock owned (L 10000)	−0.04	0.00
	(0.05)	(0.03)
Total cultivated land (ha)	−0.05	−0.03*
	(0.04)	(0.02)
Education level of household head	−0.12***	−0.06**
	(0.04)	(0.02)
Other covariates		
Household size	−0.04***	−0.01*
	(0.02)	(0.01)
Household head under 30	0.05	0.08
	(0.10)	(0.05)
Household head over 60	−0.12	−0.08
	(0.11)	(0.06)
Household head is widow(er)	0.23*	0.10
	(0.13)	(0.06)
Household received transfer from another hh last year	−0.06	−0.05
	(0.08)	(0.04)
Household received support from government last year	0.09	0.01
	(0.08)	(0.04)
Household received support from NGO last year	0.15	−0.01
	(0.10)	(0.05)
Household holds savings	−0.21**	−0.08
	(0.10)	(0.05)
Household took loan in past 12 months	0.04	0.03
	(0.07)	(0.04)
Constant	4.47***	0.96***
	(0.17)	(0.08)
Number of observations	834	834

1. OLS estimates with robust standard errors. Statistical signficance denoted * = 10%, ** = 5%, *** = 1%.
2. The asset index is created using PCA on 35 binary asset variables indicating whether the household owns each given asset. 0.105 of the overall variation is explained by the first component.
3. The vulnerability to reductions in food indicator is an index created using PCA on 6 variables: Whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating and/or skipped/reduced meals, and how frequently this happened. 0.612 of the overall variation is explained by the first component.
Source: Authors' analysis based on own data collected.

TABLE A4. Regressions - Peru

	(1) Group number in PWR (higher = poorer)	(2) Complete TUP targeting (1=poorest, 0=not poorest)
Poverty metrics		
Total weekly consumption per adult equivalent (10 S)	−0.04*	−0.03***
	(0.02)	(0.01)
Asset index	−0.06***	−0.03***
	(0.02)	(0.01)
Vulnerability to reductions in food consumption	−0.02	−0.01
	(0.02)	(0.01)
Total value of livestock owned (1000 S)	−0.10***	−0.03***
	(0.02)	(0.01)
Total cultivated land (ha)	−0.11***	−0.04
	(0.04)	(0.03)
Education level of household head	−0.03***	−0.02***
	(0.01)	(0.01)
Other covariates		
Household size	−0.03*	−0.02**
	(0.02)	(0.01)
Household head under 30	0.40***	0.11**
	(0.10)	(0.05)
Household head over 60	−0.32*	−0.22***
	(0.19)	(0.08)
Household head is widow(er)	0.08	−0.01
	(0.11)	(0.06)
Household received transfer from another hh last year	0.03	0.03
	(0.09)	(0.05)
Household received support from government last year	0.26***	0.12**
	(0.09)	(0.05)
Household received support from NGO last year	0.17**	0.03
	(0.08)	(0.04)
Household holds savings	0.16*	0.09**
	(0.08)	(0.04)
Household took loan in past 12 months	0.04	−0.02
	(0.09)	(0.04)
Household suffered an income shock in the past 12 months	0.08	0.15***
	(0.07)	(0.04)
Communal participation index	0.05	0.00
	−0.04	−0.01
Number of potential lenders in the community	0.04**	0.03***
	(0.02)	(0.01)
Number of times attended communal meetings in past 12 months	0.02*	0.01**
	(0.01)	(0.01)
Self-reported economic status (1-10)	−0.01	0.00
	(0.00)	(0.00)

(Continued)

Table A4. *Continued*

	(1) Group number in PWR (higher = poorer)	(2) Complete TUP targeting (1=poorest, 0=not poorest)
Constant	−0.10***	−0.02
	(0.03)	(0.01)
Number of observations	3.74***	0.96***

1. OLS estimates with robust standard errors. Statistical signficance denoted * = 10%, ** = 5%, *** = 1%.
2. The asset index is created using PCA on 51 binary asset variables indicating whether the household owns each given asset. 0.115 of the overall variation is explained by the first component.
3. The vulnerability to reductions in food indicator is an index created using PCA on 6 variables: Whether an adult reduced/skipped meals, how frequently this happened, whether an adult went an entire day without eating, how frequently this happened, and whether a child under 16 went a whole day without eating, and how frequently this happened. 0.522 of the overall variation is explained by the first component.
4. The community participation index is a standard z-score index, standardizing the scores of 7 variables related to participation in different community organizations to the control mean.
Source: Authors' analysis based on own data collected.