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In Light of What They Know

How Do Local Leaders Make Targeting Decisions?

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Abstract

This paper analyzes how local leaders make targeting decisions in the context of a public workfare program in the Lao People's Democratic Republic. The study finds that village heads are progressive in their targeting, prioritizing the poorer households in their villages. The study benchmarks this decentralized selection to the common alternative proxy means test method and finds that village heads are at least as progressive as a proxy means test method approach. To illuminate what poverty-related information village heads could plausibly be incorporating into their internal selection decisions, the study designs and administers a set of exercises for village heads to rank villagers on land ownership, access to nutrition, and experience with recent shocks—indicators that are likely to differ in their observability to village heads and could plausibly be associated with need for public support. The study finds that village heads' perceptions, as revealed through the ranking exercise, differ substantially from actual levels reported in surveys of the villagers themselves. The study then uses a data-driven machine learning approach to identify the predictors of village head selection. It concludes that village heads rely on a combination of easily observable household characteristics, forming a holistic impression of household welfare, rather than specific indicators like actual land ownership, nutrition, or economic shocks.

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In Light of What They Know: How Do Local Leaders Make Targeting Decisions?[1]

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1. Introduction

Targeting of social programs by local leaders, fully or in combination with some other targeting method, has been at the core of development policies and programs for many years. The discussion of the merits and perils of this approach to targeting has been comparably long. Recently, the COVID-19 pandemic has necessitated quick and effective emergency assistance delivery to those most affected, bringing new relevance to the old debate.

Indeed, there are several strong arguments in favor of this approach. Local leaders – individuals deeply embedded in the context of the lives of potential beneficiaries – may have better information about the community and relative needs of its residents (Conning and Kevane 2002; Subbarao et al. 2012). Reliance on local leaders also presents an opportunity to save resources needed for collecting information to implement alternative targeting methods, such as proxy means tests, which are often more data intensive (Alix-Garcia et al., 2019). Finally, selection of beneficiaries by a trusted member of the community may be easier to understand than selection based on a more technical approach,[2] and thus result in greater acceptance of targeting results by the community (Alatas et al., 2012).

On the other hand, vesting power of beneficiary selection in the hands of several community members may result in nepotism and elite capture. This has been an important concern for reliance on targeting by local leaders. There is no consensus in the literature on the extent of and welfare losses from elite capture in targeting of social programs by local leaders. Kilic et al. (2013) find evidence of nepotism when analyzing the distributional effectiveness of the Malawi Farm Input Subsidy Programme (FISP). Their results suggest that the relatively well-off and locally well-connected are more likely to access the program where targeting decisions are largely made by village chiefs. Analyzing the same program but using a different measure of poverty, Basurto, Dupas and Robinson (2019) suggest that the consequences of nepotism are likely to be small: a PMT would not do better. This result corroborates an earlier finding from Alatas et al. (2013) in Indonesia, who suggest that although elite capture exists in the distribution of village welfare programs, eliminating it entirely would only marginally improve welfare gains from governmental programs.[3]

Although a key focus of prior research, elite capture is not the only reason why village leader selection for social programs may lead to sub-optimal targeting of beneficiaries. Notably, the dominant approach to evaluating the effectiveness of targeting is comparison of selected beneficiaries with the members of the community deemed the "poorest" according to some poverty indicator. This common metric for effectiveness in the research literature may differ from the metric in the mental model guiding the village leader selection process for several reasons. First, the set of the poorest will clearly depend on the indicator of poverty used, which is ultimately a subjective decision. Alatas et al. (2012) demonstrate that relatively worse performance of community leaders targeting compared to PMT stems from the fact that they use a different definition of poverty. Second, village leaders may use a set of selection criteria other than poverty indicators because they are optimizing for a different metric of effectiveness. For example, Basurto, Dupas and Robinson (2019) show that village chiefs target fertilizer subsidy distribution based on

[2] Roopnaraine and Adato (2004), Brown et al. (2016) find that complexity of the PMT-based selection leads to challenges of acceptability since non-beneficiaries may find it difficult to understand why they were not selected while others were. Cameron and Shah (2014) find that using PMT in a cash transfer program in Indonesia led to distrust of local administrators, erosion of local social capital, and even an increase in crime rates.

[3] By less than 1 percent.

expected productivity. The authors further demonstrate the presence of meaningful intra-village transfers, suggesting that in the presence of these transfers allocating fertilizer subsidy to more productive households may be a superior selection criterion compared to targeting based on poverty status.

Even if village leaders were optimizing targeting of the poorest community members according to some objective definition of poverty, the effectiveness of their selection will be limited by the information available to them. Although local leaders are immersed in the life of the community, they may not have the same level of detailed information on every household that an enumerator sent to recover this information could retain. Although lack of information is a straightforward and universally plausible constraint on targeting efficiency there is a notable lack of research on the topic. To our knowledge, the only study that tests this information hypothesis is Alix-Garcia et al. (2019) in which the authors find that local leaders actually do provide accurate information on households, but acknowledge that the accuracy of their information may vary by context; for example, their information may be less accurate in larger and more dispersed communities.

In this context, our paper attempts to make a threefold contribution to the literature on targeting by local leaders. First, we contribute to the body of evidence addressing traditional metrics of effectiveness of local leader targeting by answering two questions: i) do they select worse off community members? ii) How well does their selection compare to alternative approaches, including the canonical technical approach of PMT? Second, we attempt to shed light on the process of selection. Specifically, we explore what characteristics and criteria best rationalize local leader led beneficiary selection. This aspect of the paper contributes to the evidence that local leaders may use a different definition of poverty compared to program designer/policy maker. We test whether, in selecting the poorest, local leaders are more likely to rely on information about assets, likelihood of hunger, or subjective perception of immediate need. While assets are likely to capture long-term welfare, likelihood of hunger is a better proxy of current welfare, and perception of immediate need may reflect exposure to shocks. Third, we check whether local leaders rely on accurate information when making targeting decisions: i.e. whether what they know about household's landholdings corresponds to landholdings as reported by the household.

Another contribution of our paper is in analyzing the effectiveness of targeting by local leaders in the specific context of a public works program. We focus on a program in the Lao People's Democratic Republic where village heads played an important role in selecting program beneficiaries. Constraints on effective targeting are likely to differ by program type. For example, the likelihood of nepotism may be higher for programs where there are no implicit participation costs (e.g. unconditional cash transfers, food vouchers), compared to programs with strings attached, such as public works programs, especially if working conditions are difficult. In contrast to the workfare setting of our study, much of the existing targeting literature is focused on conditional cash transfers, including work focused on the targeting of health insurance (Alatas et al., 2012), food subsidies (Alatas et al., 2012 and Basurto, Dupas and Robinson, 2019), and fertilizer subsidies (Basurto, Dupas and Robinson, 2019).

We collect detailed welfare data on those who were identified as eligible to participate in the program by the village heads, as well as on a random sample of households from the same village. We also administer a series of ranking exercises to the village heads, aimed to elicit guiding principles for their selection, and to assess the quality of information they rely on. The paper is organized as follows: the next section describes the Road Maintenance Groups program, the process of beneficiary selection and provides background on the position of village heads. Section 3 presents the study's data. Section 4 analyzes whether the village heads indeed selected poorer households in the village. Section 5 explores what village heads prioritize when making selections. Section 6 analyzes what information they use. Section 7 explores the question of acceptability of the village heads' selection for other community members. Section 8 concludes.

2. Road Maintenance Groups Program and Beneficiary Selection

In rural Lao PDR, remote villages are connected to laterite highways via dirt access roads. Access roads are built by government-hired contractors but typically fall into extreme disrepair and often become unusable within a couple years due to a harsh rainy season. The Road Maintenance Group (RMG) program is a pilot program set up by Lao PDR Poverty Reduction Fund (PRF)[4] with the dual objectives of providing an income-earning opportunity to in-need households and extending the lives of the access roads. The RMG program trains participants to carry out road maintenance activities that do not require heavy machinery and subsequently employs them to provide basic road maintenance services throughout the year. PRF designed the program to be part-time. In order to support women's empowerment, PRF only hires women to work in RMGs.

The villages participating in the RMG program are poor and have few opportunities for wage work. Compared to rural households in the nationally representative sample in the Lao Expenditure and Consumption Survey (LECS) V, collected in 2013, RMG villages were poorer across a range of indicators including housing composition, ownership of durables, and nutrition.[5] Only 17% of working-age individuals in these villages had paid work outside the household at the start of the program. The RMG jobs were therefore highly attractive to populations living in these villages, but the program aimed to allocate the RMG spots to the poorest households in the villages.

The village heads played an important role in this allocation. First, the village heads were responsible for publicizing the program and inviting households to the registration event, acting to some extent as gatekeepers for information about RMGs. Baird, MacIntosh and Ozler (2013) provide an example of informational elite capture. Their analysis of targeting effectiveness of Tanzania's flagship CDD program suggests that wealth, education, access to media, and political engagement are positively correlated with awareness of the program, which is a necessary condition for benefitting from it. Such lack of access to information results in only mildly pro-poor targeting.

Second, the village heads contributed to the selection of beneficiaries through updating their poverty ranking. Specifically, beneficiaries for the RMG program were selected through a two-step process in June 2018. In the first step, those eligible to participate in the program were identified. In the second step, as demand for the program exceeded the number of RMG jobs, a lottery (lucky draw) was carried out to

[4] PRF is housed under the Government Office of Lao PDR. Its mission is to apply a community driven development approach to reduce poverty in Lao PDR, with a focus on rural populations, by improving infrastructure and access to services and resources.

[5] Authors' calculations using the baseline data for the RMG impact evaluation and LECS V. Available upon request.

divide all the eligible and interested into beneficiaries (RMG) and a waitlist (WL).[6] In this paper, we focus on the first step of the selection process. In order to qualify as 'RMG-eligible', registrants had to be at least 18 years old, female, and able-bodied. Women from poorer households were given priority based on the household poverty rank (poorest, poor, middle income and better off). Specifically, women in the bottom two poverty ranks (poorest and poor) were first granted entry. If the village quota for RMG-eligible was met, the process ended. If the quota was not met, women from the next poverty rank (middle-Income) were then entered. If the quota was still not met, women from the next poverty rank (better-off) were also entered. Eligibility was thus determined by poverty bracket; no distinction was made between women of the same bracket.

The poverty status of each household was determined through a process that combined PMT, community-participation, and village-head updating. Household poverty ranks were originally constructed by PRF in 2016 based on PMT. In each village, there was a multi-day participatory process of PMT verification and adjustment by which households were assigned poverty ranks. During the registration process for the RMG program in 2018, village heads updated these rankings to account for changes in the two years since the original ranking. Twenty-four percent of households changed their poverty rank as a result of this updating.

Figure 1 plots the original ranking against ranking by the village heads in 2018. Overall, 174 households changed poverty category.[7] Among them, 74 (10 percent) became less poor: moved from poorest to poor or middle income, from poor to middle income, or from middle income to better off. One hundred (14 percent) became poorer, moving from better off to middle income, poor and poorest, from middle income to poor and poorest, or from poor to poorest. If these movements reflect real changes in household welfare, reliance on village heads is efficiency improving. It would allow PRF to allocate the RMG program considering recent changes in household welfare, without carrying out another PMT test and community validation, which at the moment of the RMG program launch were prohibitively expensive. On the other hand, the change in poverty ranking of 24 percent of interested households may reflect nepotism, or as discussed above, be based on a definition of poverty different from the one preferred by PRF.

A priori, we believe the former hypothesis to be more likely. First, village head is an elected position. Specifically, the village head is first elected by villagers, and then approved by district governor. The term lasts for 3 years, and village head can be re-elected. Notably, the villagers can report to the district management office, if they are not happy with the village head, and request re-election/re-appointment. Consequently, there are accountability mechanisms that create disincentives to engage in nepotism.

Second, assessment of poverty status of the villagers is included in responsibilities of village heads. Decree on the Criteria for Poverty Graduation and Development outlines six criteria for graduating from poverty, and village heads should be receiving training on these criteria. These criteria are: (1) have safe and strong housing; (2) have assets and equipment necessary for their livelihoods and income generation; (3) have

[6] PRF agreed to introduce randomized assignment of jobs with two objectives: (i) fair and transparent allocation of the jobs; (ii) possibility to carry out an impact evaluation of the RMG program. The data analyzed in this paper were collected as part of the IE.

[7] We have the original 2016 poverty ranks for 716 households. For other 430 households, the rankings were not available. We are confirming the role of village heads in assigning these rankings.

labor, stable income or employment; (4) school age family members receive lower secondary school education; (5) have access to clean water and stable sources of energy; (6) have access to primary public health services. Decree suggests that implementing ministries should divulgate its provisions to local governments. The extent to which village heads adhere to these criteria when selecting beneficiaries in practice depends on several factors, such as success in disseminating the decree and village heads training on it, potential differences in interpretation of some of these criteria (e.g. stable employment) and village heads' access to information about these criteria for all households in the village. Lastly, village heads may still select on a different criterion, as in Basurto, Dupas and Robinson (2019), especially given that there are no formal checks of accuracy in place.

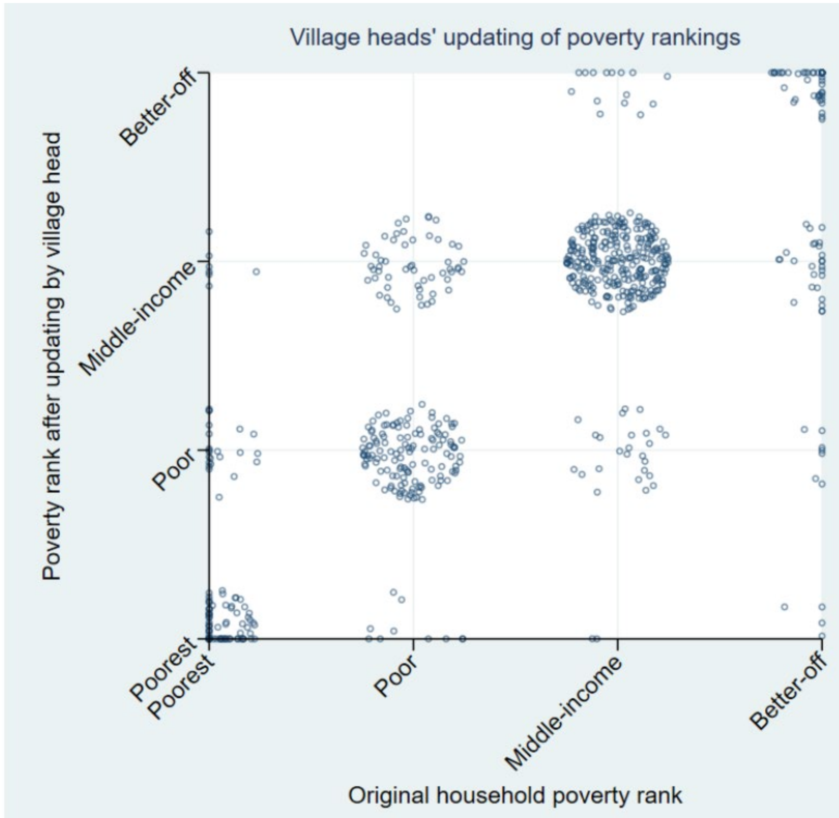
We study the outcomes of village heads selection process in 85 villages across 7 provinces in northern and southern Lao PDR where the RMG program was implemented.[8]

3. Data

To understand how village heads determined household eligibility and to assess the quality of their decisions in terms of targeting the poor, RMG baseline data collection included two targeting assessment components. First, in addition to collecting data on RMG and WL households that form the treatment and control groups for the impact evaluation, we administered the same survey to a Random Sample (RS) of village households with a woman of eligible age to participate in the RMG program (limited for simplicity in the random sample to ages 18-55). Households selected into the random sample could be replaced if they did not have a female household member of eligible age, if they had moved out of the village, if they could not be located after multiple attempts spanning at least two days, if they refused to participate, or if they were already part of the RMG or WL sample.[9] This sampling strategy enables comparison of household characteristics between the RMG-eligible and RS groups to establish whether the households granted entry to the lucky draw were truly among the villages' poorer households. Second, we administered the village heads a targeting survey to probe the key factors influencing their selection of welfare beneficiaries and to understand their underlying perceptions regarding what constitutes poverty.

[8] Although the RMG program was implemented in 86 villages, one village was dropped from the analysis because recruitment of beneficiaries there deviated from the model described above.

[9] There was a total of 274 replacements: 151 households were replaced because they were already in the RMG/WL sample. The remaining replacements were due to: absence of women of eligible age in the household (36); households were absent due to harvesting season (20); households were no longer in the village (33); refusal (14) and other reasons, such as mental illness or temporary absence (20).



The data analyzed in this paper were collected as the baseline for the impact evaluation in September–October 2018.[10] Baseline data collection included household, individual, and targeting questionnaires. We administered the household questionnaire to the RMG, WL, and RS households. RMG and WL members completed the individual questionnaire in full, and, in RS households, a woman of eligible age to participate in the RMG program answered select sections. The household and individual questionnaires included the following modules: labor force participation, household income, housing conditions, durable possessions, land ownership, economic shocks, nutrition, and personal connections with the village heads. Our survey budget did not allow for inclusion of a consumption module. Under the baseline data collection, 1,888 households were surveyed: 333 RMG (treatment) households, 813 WL (control) households, and 742 RS households. For simplicity we will be referring to the groups of RMG or WL jointly as RMG-eligible.

Each village head completed a targeting survey for a total of 85 respondents. The targeting questionnaire asked the village heads to rank 15 village households along a set of poverty-related indicators. The 15 households were comprised of 5 RMG, 5 WL, and 5 RS households, randomly chosen from the village's pool of survey respondents.[11] To prevent fatigue from the multiple rankings, the women's names were written on slips of paper, which the village head reordered for each ranking. The 85 village heads ranked

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[10] Results of program impacts on household income, nutrition, women's empowerment, and other outcomes will be shared in a separate paper.

[11] Sixteen villages did not have enough RMG, WL, and RS members to rank 15 individuals because of either smaller RMG-eligible memberships or participant absence at time of survey. In these cases, the maximum number of households available for ranking was specified in the instructions. Eight villages had 14 households ranked, 5 villages had 13, 2 villages had 12, and 1 village had 9.

a total of 1,245 households. There were two types of ranking questions: RMG priority ranking and ranking based on specific criteria:

"RMG Priority Ranking":
Please rank who you would prioritize to join the RMG if it were solely up to you and not determined by eligibility and a lottery. Start with the highest priority to the least priority. For example, if I were in the list and you really thought I should receive the RMG job, you would rank me number 1. If you think I am the last person in the list you would give the job to, rank me (total number in the list).[12]

Criteria Rankings:
- Rank who owns the least to most square meters of land, agricultural and residential land combined.
- Rank the likelihood that, in the last 12 months, the person or someone in her household was hungry but did not eat because there was not enough rice or food at home, and not enough money or other tradeable goods to purchase rice or food. Start with the person or household most likely to have had been hungry but did not eat.
- Rank who needs the most to least help right now.

The variety of data collected, including actual data on selection, respondent self-reports, and data collected on hypothetical ranking by village heads, combined with an intention sampling design that includes both selected and non-selected among eligible and a random sample of villagers, enable us to explore both the actual targeting by village heads, the proximate inputs into the targeting choices, and the potential information constraints that may limit the ability of village heads to target the poorest households in their villages.

4. Do village heads effectively select poorer households for participation in RMGs?

Given the extensive baseline surveys administered to the RMG-eligible and the RS, we can compare them on a wide range of dimensions, including income, assets, land holding, etc. Notably, the baseline questionnaires did not include a comprehensive consumption module, which elsewhere is commonly used for assessing poverty status. Table A1 in the Appendix shows 127 variables describing the participants' basic demographic characteristics, household composition, income, possession of durables and livestock, housing conditions, nutrition, and experience of economic shocks, available in our survey.

To reduce dimensionality and address the likelihood of Type I errors in our numerous possible comparisons between the RMG-eligible and RS groups, we follow Katz, Kling and Liebman (2007) and Andersen (2008) by constructing composite z-scores and adjusting the p-values for multiple hypothesis testing. The z-scores of the individual variables are calculated and then averaged by category to construct composite z-scores. The z-scores of variables assumed to be negatively correlated with wealth are inverted. Altogether, we construct 7 composite z-scores to encompass broad dimensions of welfare: land and buildings ownership, household composition, durables ownership, livestock ownership, housing conditions, nutrition, and shocks. We also test for differences in household per capita total income. We apply Bonferroni correction to adjust p-values for the differences in means tests, to further reduce the

[12] Sixteen villages did not have enough RMG, WL, and RS members to rank 15 individuals because of either smaller RMG-eligible memberships or participant absence at time of survey. In these cases, the maximum number of households available for ranking was specified in the instructions. Eight villages had 14 households ranked, 5 villages had 13, 2 villages had 12, and 1 village had 9.

likelihood of false rejections of the null hypothesis of no difference due to multiple hypotheses testing. Table 1 shows the t-tests and provides more details on variables included in specific z-scores.

Table 1: Differences in household welfare between RMG-eligible and Random Sample

	RMG-eligible obs.	Random Sample obs.	RMG-eligible mean	Random Sample mean	Diff. (RMG-eligible – Random Sample)	P-val	Bonferroni corrected P-val
Land and buildings ownership	1146	742	-0.035	0.054	-0.0890**	0.004	0.033
Household composition	1146	742	-0.0176	0.0272	-0.0448	0.013	0.102
Durables ownership	1146	742	-0.0388	0.0599	-0.0987***	0.000	0.000
Livestock ownership	1146	742	-0.0449	0.0693	-0.1142***	0.000	0.001
Total income per HH member (USD PPP)	1146	742	381.919	480.733	-98.8140**	0.004	0.032
Housing conditions	1146	742	-0.0131	0.0202	-0.0333*	0.008	0.066
Nutrition	1146	742	0.0097	-0.0149	0.0246	0.084	0.669
Exposure to shocks	1146	742	0.0039	-0.0059	0.0098	0.666	1.000

* p<0.1 ** p<0.05 *** p<0.01

RMG-eligible = 1146 observations. Random Sample = 742 observations. All household characteristics are shared as composite z-scores, except for total income per HH member. Variable included in composite z-scores are: Land and buildings: total area of residential and agricultural land, plus total number of buildings owned by each household. Household composition: dependency ratio, household head age, gender, ethnicity, and education. Durables ownership: ownership of household goods, including cars, TVs, refrigerators, etc. Livestock ownership: numbers of productive animals owned, including cows, buffalos, chickens, etc. Total income per capita: sum of 9 types of income divided by the number of household members. Housing conditions: number of rooms; flooring, roofing, and wall materials; kitchen location and structure; access to water; etc. Nutrition: balls of rice, kg of meat, number of days dairy eaten, etc. Exposure to shocks: experience of health, business, and agricultural shocks.

Table 1 suggests that the RS households are significantly better off than RMG-eligible households, typically owning more possessions, having higher quality housing, and generally experiencing better well-being as viewed through these variables. It is important to remember that the pool of RMG-eligible reflects a combination of targeting methods: self-targeting as well as targeting by village heads. Village heads affected the selection process through (i) sharing information about the program; (ii) updating poverty status.[13] However, only women who were also interested to join RMGs entered the lucky draw and are captured in our sample as RMG-eligible. For simplicity and clarity of exposition, we may refer to this sample as village head selection, though formally speaking this implies village head selection conditional on self-selection.

Overall, Table 1 suggests that the RMG program effectively targeted poorer households within villages. We next compare actual selection to a hypothetical selection based on PMT used by the Government of Lao PDR to identify the poor for participation in social programs. This PMT index was developed by the World Bank and Government of Lao PDR, following administration of LECS V in 2012-2013 (Pimhidzai et al. 2014). It relied on regression analysis of household consumption on surveyed household characteristics. The model aimed to accurately distinguish between poor and non-poor households. Non-significant characteristics were removed from the model; characteristics that minimized misidentification of poor and non-poor households were kept. Index variables and weights were determined based on the regression outcomes. Households scoring below 64 were classified as poor. Table A2 in the Appendix provides the complete list of variables used in the PMT index (World Bank forthcoming).

When we compare village head selection with those selected through PMT, we find that, though both methodologies selected approximately the same number of beneficiary households, they disagree on which households should benefit in 44% of cases. The magnitude of this disagreement holds true whether one considers the full sample of 1,888 study households (Table 2) or only 1,245 households ranked in the village head targeting survey (Table A3 in the Appendix). Although we expect differences in how PMT and village heads identify poor households, the consensus on population poverty rates and need for welfare support is striking.

Table 2: Village heads vs PMT – Full Sample of 1,888 Households

RMG-eligible	PMT below 64		Total
	No	Yes	
No	300 (16%)	442 (23%)	742 (39%)
Yes	401 (21%)	745 (39%)	1,146 (61%)
Total	701 (37%)	1,187 (63%)	1,888 (100%)

The discrepancy in identification of the poor by the two methods leads us to further assess their targeting accuracy. We compare household characteristics typically indicative of wealth status between the eligible and ineligible/ poor and non-poor groups under village heads selection and PMT. We expect the more accurate method to produce a larger difference in observable welfare characteristics.

To reduce the complexity of analyzing overall wealth disparities through numerous household characteristics, we again construct composite z-scores similar to those we used for comparisons of RMG-

[13] Thus, the selection may also reflect PMT and community validation carried out in 2016. However, based on the field supervisors' reports, the changes in poverty ranks were substantial.

eligible and random sample in Table 1. One important difference in the construction of these z-scores is that now we exclude variables used to construct the PMT index. Including these variables would give unfair advantage to the PMT method: we would expect to observe larger differences between eligible and non-eligible according to PMT on the variables underlying its construction.[14]

Figure 1 plots the differences in z-scores between RMG-eligible and RS, against the differences between poor and non-poor according to PMT, including 90% confidence intervals. The gaps between groups according to the two methods suggest that PMT outperforms RMG-eligible selection in identifying poor households. The differences in means are significantly larger under PMT for 4 out of 8 analyzed indicators.[15] RMG-eligible selection performs better than pure random assignment to eligible vs. ineligible groups, but it is less accurate than PMT. T-tests for differences in z-scores for eligible and not eligible according to two selection methods are shown in Table A3 of the Appendix.

However, village heads were identifying the poorest households from within a village, not across the sample. If we replicate this analysis by calculating z-scores within village, rather than across the entire sample, village head selection and PMT appear to provide equivalent levels of accuracy. Figure 2 shows the differences in z-scores between eligible and non-eligible according to the two methods, including confidence intervals.[16] The overlap of confidence intervals suggests that we cannot reject the hypothesis of no difference in the magnitude of the welfare gap between eligible and non-eligible according to the two methods. Table A4 in the Appendix shows corresponding t-tests.

In the analysis based on village-level z-scores, easily observed variables perform better under village heads selection, while factors less visible to the public eye perform better under PMT. For example, livestock and durables ownership are negative and significant for both methodologies, but the difference in means is greater under RMG-eligible selection. Conversely, nutrition and income, the status of which might be known only to household members, perform better under PMT; the difference in the nutrition composite z-score t-test is negative and significant only for PMT, and the difference in means for income is significantly larger under PMT.

The village-level results suggest that when organizing beneficiary selection to meet the needs of the local context, the village heads selection was effective through leveraging the heads' familiarity with the households. This familiarity, however, was limited when it came to assessing more obscure or private household characteristics. In such cases, the rigorous PMT methodology based on detailed survey data performed better.

We must also note that less-poor households (ranked 'Middle-income' or 'Better-off') were included in the RMG-eligible list in some villages in order to satisfy village quotas for the program. We would expect the inclusion of these non-poor households to worsen the average performance of the village heads selection. In a setting where the quotas for road maintenance were satisfied by the households from the

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[14] Comparison of RMG eligible observations and random sample using this restricted selection of variables provides results similar to those shown in Table 1. See Table A5 in the Appendix for all comparisons.

[15] Please note, income per household member is shown as z-scores in Figure 1 in order to display the measure along with the other indicators in the graph, but the actual difference for the RMG-eligible vs. RS is -0.1426 ($p<0.01$) and, for PMT poor vs. nonpoor, -0.8213 ($p<0.01$).

[16] Income per household member is again shown as a z-score to aid the graph. Actual difference between RMG-eligible and RS is -0.2160 ($p<0.01$). Between PMT poor and nonpoor, the difference is -0.5417 ($p<0.01$).

lowest poverty ranks, we would expect the village heads selection to fare slightly better on welfare comparisons.

Figure 1: T-tests of composite z-scores by VHT and PMT targeting methods – Across the full sample

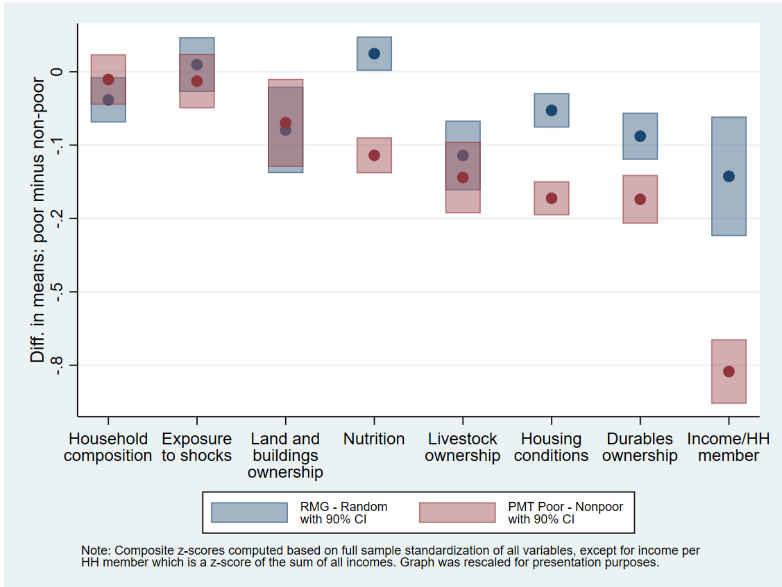
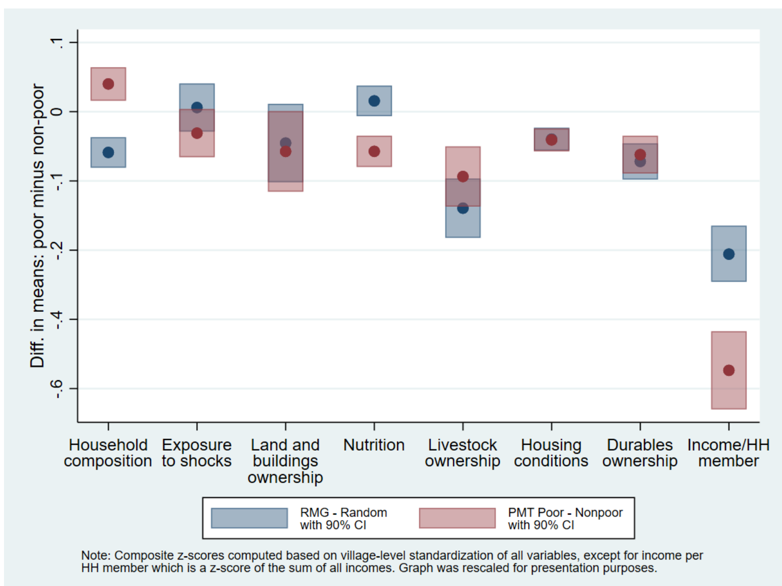


Figure 2: T-tests of composite z-scores by VHT and PMT targeting methods – Grouped by village



5. How do village heads prioritize potential beneficiaries for RMG selection?

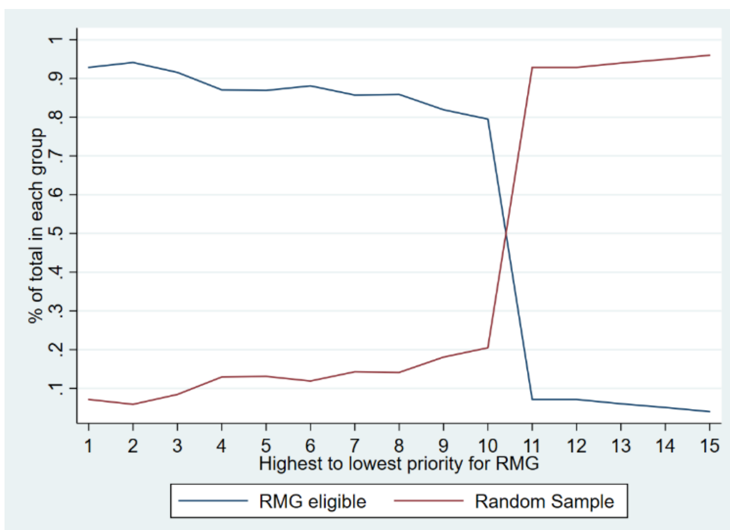
We next attempt to understand the mechanism behind village heads' selections. To do so, we use the ranking exercises we administered to the village heads. The objective of asking the village heads to choose among the pooled list of RMG-eligible and randomly selected households was two-fold:

First, we check whether village heads' views on who should be working in RMGs are aligned with PRF-imposed targeting criteria. It is conceivable that village chiefs may disagree with making household poverty level a core criterion for selecting RMG participants. For instance, village heads may be concerned with the quality of public goods delivered and prioritize women's ability to do the job. To achieve this, we emphasize "if it were solely up to you and not determined by eligibility and a lottery" when asking village heads to rank households in order of priority for RMG jobs.

Second, we aim to understand the driving factors behind the village heads' selection. The ranking exercise helps us in several ways. First, we can compare RMG priority ranking with rankings on three criteria, which broadly capture different potential approaches to prioritizing the poor: ranking on agricultural and residential land, on likelihood to experience hunger, and on the need of help. Ranking on assets is likely to capture long-term poverty status, ranking on the likelihood of hunger may potentially capture greater severity of poverty, and ranking on the need of help is likely to capture exposure to shocks. Correlating RMG priority ranking with rankings on different dimensions of poverty will provide information on which dimensions of need village heads prioritize when selecting for RMGs.

As Figure 3 makes clear, the RMG priority ranking is largely aligned with the village heads' selection of households eligible to enter the RMG job lucky draw. In Figure 3, the x-axis shows the RMG priority ranking and the y-axis shows the percentage of RMG-eligible and RS households occupying each spot in the priority ranking. For example, among all observations ranked as #1 priority, slightly more than 90% are from the RMG-eligible group and less than 10% are from the RS. At least 80% of the first 10 priority ranking spots are filled by RMG-eligible households, typically leaving the last 5 spots in the priority ranking for the 5 RS households included in the ranking exercise.

Figure 3: Fraction of RMG-eligible and Random Sample in each rank position



Although the fact that village heads assign RMG-eligible households to the highest positions in the RMG-priority ranking may suggest their agreement with the principle of selection into RMGs based on poverty status, it is important to note that there may also be an anchoring effect. We conducted the ranking exercises shortly after actual selection into RMGs took place. The village heads may have been inclined to select women they already knew to be in the RMG-eligible group.

We next proceed to exploring how the three criteria rankings (land holdings, likelihood of being hungry, and need for help) correlate with the RMG priority ranking. Does a higher ranking among one of these criteria create a greater likelihood of being ranked higher in the RMG priority ranking? Table 3 demonstrates a regression of likelihood of being ranked higher for RMG priority on each of the three criteria in columns (1) – (3) and the three rankings together in column (4). Regression in column (5) controls for RMG-eligibility status: a dummy equal to 1 if the household is RMG-eligible, and 0 if it belongs to the random sample.

Table 3 reveals several interesting features about the process of village heads' selection. First, the relationship between priority ranking and each of the three ranking is significant, but coefficients are low, ranging between 0.15 (for land holdings) and 0.22 (for the need for help). Notably, association between the ranking of those who need help most and RMG priority ranking is the strongest: not only is the coefficient the highest, association between these rankings is the only one that remains significant once all three rankings are accounted for in a regression. Village heads appear to rely on some notion of the need of help when deciding on how to prioritize for RMGs.

Second, once we account for RMG-eligibility, none of the three criteria remains significant. Only designation as an RMG-eligible or RS household is significant: being eligible for RMGs is associated with decrease in rank, and consequently higher priority for RMGs in village heads' perception (please note that households are ordered from 1 to 15, one being the highest priority). This may suggest that village heads fully endorse the selection criterion proposed by PRF: household's poverty status. An opportunity to prioritize based on a different criterion does not lead to a vastly different result than their selection of RMG-eligible. However, as mentioned earlier, we cannot exclude the possibility of an anchoring effect.

Table 3: Likelihood of being prioritized for an RMG role as a function of other rankings

	Priority for RMG	Priority for RMG	Priority for RMG	Priority for RMG	Priority for RMG
Lowest to highest land holdings	0.1560***			0.0465	0.0266
	(0.036)			(0.038)	(0.028)
Highest to lowest likelihood to be hungry		0.1834***		0.0321	-0.0277
		(0.036)		(0.047)	(0.037)
Highest to lowest need for help			0.2228***	0.1751***	0.0466
			(0.037)	(0.049)	(0.040)
RMG-eligible (y/n)					-6.2117***
					(0.420)
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,245	1,245	1,245	1,245	1,245

* p<0.1 ** p<0.05 *** p<0.01

Priority for RMG regressions are calculated as highest to lowest priority: the household ranked #1 is the household that should get the highest priority. Standard errors in parentheses. The 3 criteria (land holdings, likelihood to be hungry, need for help) are ranked with #1 as the poorest or worst outcome, and improving in status as the rankings increase until the final slot, #15.

6. What information do village heads use in their targeting decisions?

Relatively weak association between RMG priority ranking and the three rankings which may capture different dimensions of poverty begs the question of whether village heads use accurate information in assigning the ranks. To check whether this is the case, we correlate village heads' ranking and ranking based on the survey data. Specifically, we correlate ranking on land with rank on the sum of land area, ranking on the likelihood of hunger with a nutrition index, and ranking on the need for help with an index constructed based on the survey data about recently experienced shocks. We use Kendall correlations, a special case of standard Pearson correlation evaluating the degree of similarity among sets of ranks (Abdi, 2007).

To check robustness, we use several measures for each of the dimensions of poverty captured in ranking exercise. For land, in addition to the sum of residential and agricultural plots, we create a composite z-score of variables related to land and building ownership, as well as the first principal component of these variables. For the likelihood of being hungry, we use a composite z-score and the first principal component of all nutrition-related questions in the survey. For the likelihood of needing help, we create a composite z-score of all survey variables related to economic shocks, and also use the first principal component of these variables. These variables provide a unique household ranking in nearly all villages. Table 4 presents the results.

Village heads' rankings of land ownership are weakly but significantly correlated with households' reported land size. Their rankings of likelihood of hunger are correlated with nutrition measures but the correlation is weaker. Rankings of need for help are not correlated with shocks. The consistent strength of land measures across ranking exercises may be explained by the fact that land is the most directly observable of the three criteria for someone outside the household.

Table 4: Correlations of rankings and household variables

	Lowest to highest land holdings	Highest to lowest likelihood to be hungry	Highest to lowest need for help
Land measures			
Size of all plots (res. and agr.)	0.149***	0.098***	0.103***
Composite z-score of land and buildings	0.150***	0.133***	0.136***
Principal component 1 of land and buildings	0.148***	0.133***	0.137***
Nutrition measures			
Composite z-score of nutrition	0.008	0.004	0.017
Principal component 1 of nutrition	0.088***	0.108***	0.090***
Shocks measures			
Composite z-score of shocks (all inverted)	-0.049**	-0.031	-0.023
Principal component 1 of shocks (all inverted)	-0.031	-0.028	-0.008
Observations	1,245		

* p<0.1 ** p<0.05 *** p<0.01

The weakness of the correlations between the three criteria and their corresponding observable characteristics indicates that village heads do not determine these rankings based solely on observable land, nutrition, and shock characteristics. Rather, the village heads may base their rankings on other information about household welfare that overlaps with the information on land, nutrition, and shocks.

The question is: what are the indicators that village heads use to decide which households have more land, are hungrier or more in need of help?

Random forest analysis facilitates this inquiry by ranking independent variables—welfare characteristics in our case—from strongest to weakest, in terms of their explanatory power to predict the dependent variable outcome—here, likelihood of being ranked highly in one of the ranking exercises (Friedman et al., 2001). It is important to note that random forest analysis determines the strength of the association, but not its direction.

In random forest regressions, the predictive power of a variable shows the extent to which a given variable, when used to predict the values of the dependent variable, contributes to the increase in the accuracy of predictions. In all four random forest graphs presented below, average increases in accuracy of predictions and the importance of a given variable are expressed relative to the most important variable, which has a value of 1. In Figure 4, for example, we can see that "Woman works in non-HH business" is the most important variable for predicting how high she is prioritized for an RMG role. An external unroofed kitchen is the next most important, with a value of approximately 0.725, roughly ¾ as predictive as whether the woman works outside the household. The scale, however, does not indicate if working outside the household makes the woman more likely to be prioritized—according to the scale, it could heavily weigh against her, as well.

Figure 4: Random forest analysis of RMG priority ranking

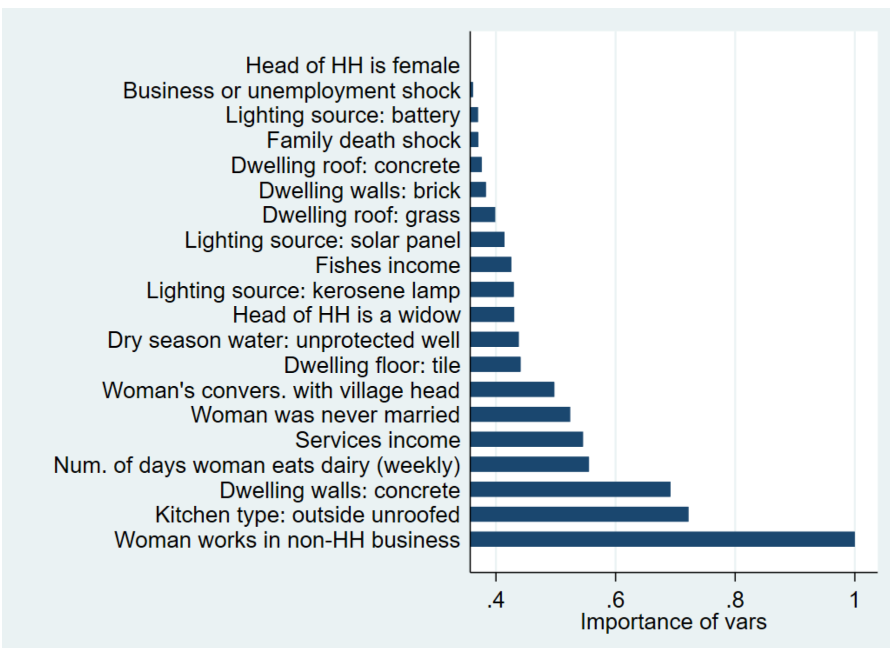
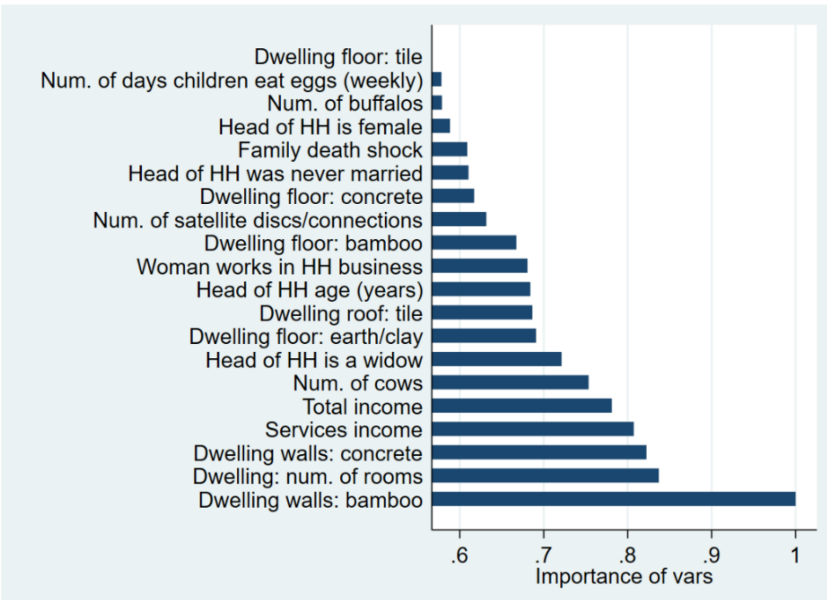


Figure 4 demonstrates that the most predictive indicators for RMG priority ranking are easily observable household characteristics, such as the woman working in a non-household business, possessing an outside unroofed kitchen, and having concrete dwelling walls. Factoring in women's work in non-household businesses might signify that the village head considered women's need for work or capability to maintain a role outside the home. Income from services is also a predictor, potentially indicating that village heads took monetary well-being into account when prioritizing RMG members. Figure 4 displays only the 20 strongest predictive indicators for RMG priority ranking; the complete list of 127 predictors is shared in the Appendix.

Figures 5-7 show the 20 most predictive indicators for each of the three criteria. Similar to the RMG priority ranking, the main predictors for the three criteria are easily observable household characteristics, plus total income. Although total income is predictive, its highest ranking is 4, for likelihood of hunger, implying that directly observable characteristics matter more than income for village heads' ranking of beneficiaries.

Figure 5: Random forest analysis of land holdings ranking



The three targeting survey criteria rankings largely share predictive indicators, though the ranking order varies between the criteria. The following 10 indicators are among the top five predictors for one or more of the three ranking criteria, and, aside from bamboo walls and female household heads, their presence likely signifies wealthier households: (i) tile dwelling floors; (ii) concrete dwelling walls; (iii) bamboo dwelling walls; (iv) female household head; (v) number of dwelling rooms; (vi) number of mobile phones; (vii) number of motorcycles; (viii) income from services; (ix) total income; (x) woman works in household business. Most of these indicators are directly observable.

Interestingly, the independent variables on land holdings do not fall among the top 10 predictors for any of the criteria, including the village heads' ranking of land ownership. This suggests that, while village heads select on observable characteristics, these are not necessarily the characteristics most directly linked even to criteria they are ostensibly ranking.

It is important to note that baseline data collection ran a few months after the RMGs had been formed and RMG work had begun, so it is possible that the RMG-eligible group reported more conversations with the village heads because they were speaking with the village heads about RMG work. However, it is also possible that there was some elite capture. We must also note that these two variables were self-reported by the survey participants, and possibility for error through misunderstanding or misrepresentation exists.

Taken at face value, though, the variables indicate minimal or no elite capture, nepotism, or favoritism in the village head targeting.

Figure 6: Random forest analysis of the likelihood of being hungry ranking

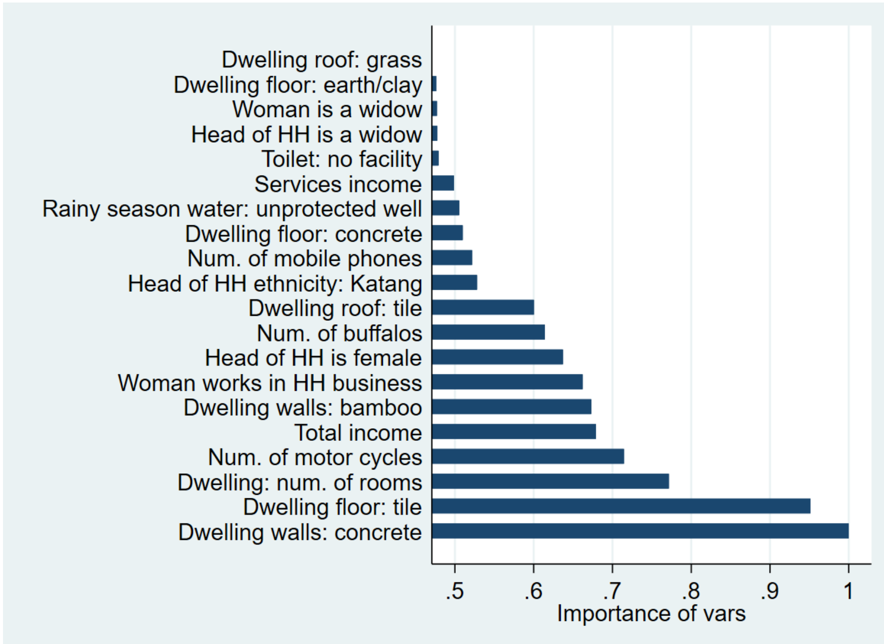
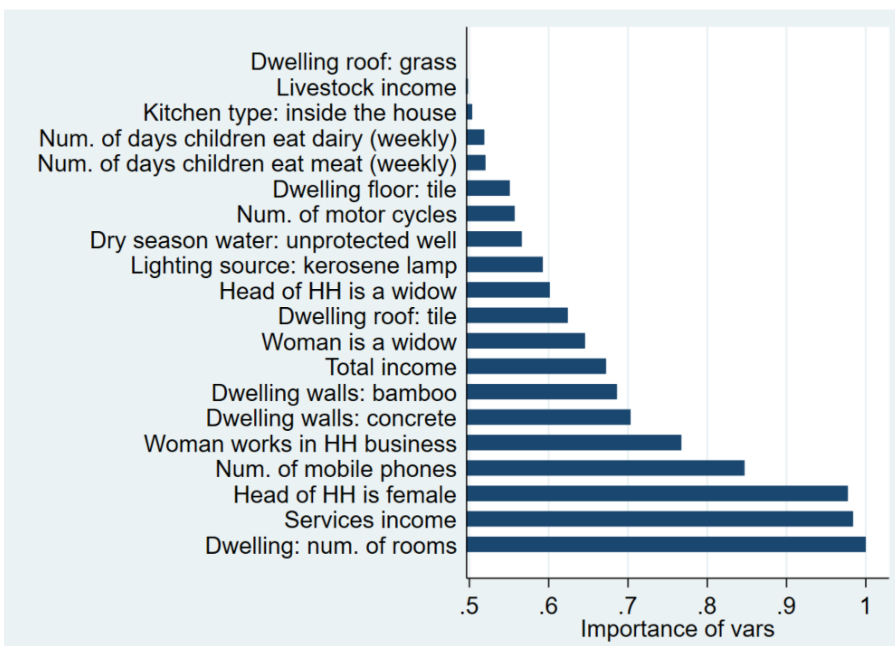


Figure 7: Random forest analysis of the need for help ranking



Random forest analysis suggests that the village heads' ranking of households on specific criteria is based on a holistic impression of poverty gathered from a host of observable characteristics. This holistic assessment has precedence. Alatas et al. (2012) write that community representatives assigned to select program beneficiaries may employ holistic measures of well-being that account for local context, including context-specific understandings of poverty and of who needs help the most. The holistic measures are based on visible household characteristics and potentially on observable community characteristics, as well.

7. Is the village head's role in selection acceptable to the population?

While discussing the random forest analysis of ranking predictors, we observed that there appears to be little or no evidence of elite capture in the village head selection process. Analyzing the performance of village head targeting against PMT suggested that the village heads are better able to incorporate local knowledge, tailoring beneficiary selection to the local context. To access effectiveness of village heads targeting, one more question must be answered: do community members consider village head targeting to be a legitimate method for allocating community resources?

Our survey included two questions that facilitate this inquiry: 1) Do you feel that your village head has a good understanding of how rich or poor most of the households are in your village? 2) When the RMG in this village was selected, the village head advised the selection team on the poverty status of the applicants. Is this a fair practice? These questions were administered to WL and RMG households only – unfortunately, we did not ask the RS households. Below we present the results separately for RMG and WL women, considering that being selected into/out of the program, even if as a result of lottery, may affect RMG/WL women's view on the overall fairness of the selection process and the role of village heads.

Both RMG and WL women indicate strong confidence in the accuracy and fairness of village head targeting. Sixty-five % of RMG and 67% of WL women thought the village head "absolutely" had a good understanding of the villagers' wealth. An additional 22% of WL and 19% of RMG members thought the village head understood "to some degree." There was no significant difference between their responses.

Similarly, the RMG and WL women considered the village head's role in beneficiary selection to be fair. Sixty-eight % of WL and 70% of RMG thought it was "absolutely" fair, and 18% of WL and 17% of RMG thought it was fair "to some degree." Again, there was no significant difference in answers between WL and RMG.

Unfortunately, we did not ask the RS households these questions. This leaves open the possibility that those who were admitted to the lucky draw were satisfied with village heads involvement in the process even if they did not ultimately benefit from the program (i.e. were in the control group), whereas those denied the chance to enter the lucky draw could be dissatisfied with the village heads' role. It is also possible that our respondents indicated satisfaction out of acquiescence bias or hesitation to admonish authority figures. Future studies can inquire more deeply into community-wide acceptance of village head targeting.

8. Conclusion

We studied the targeting performance of a multi-province workfare program in rural Lao PDR that used a combination of methods to target poorer women interested in the opportunity to do paid work. To identify poorer women, the program used poverty ranks constructed using PMT and community ranking in 2016 and updated by village heads during the program registration process in 2018. Our results suggest that the program was successful in identifying beneficiaries significantly worse off than a random sample of households from their villages. Moreover, comparison with a hypothetical pure-PMT demonstrates the two methods to be roughly equivalent in their ability to identify poorer households within a village.

Further, we shed light on what information village heads use to assess the welfare status of households. We asked village heads to rank households by different welfare criteria and then compared these data to household survey data. We find that village heads seem to base their assessments of specific criteria like household land ownership, likelihood of being hungry and likelihood of needing assistance on a holistic impression of household welfare, rather than specific indicators like actual land ownership, nutrition or economic shocks. Using random forest analysis, we find that their rankings are best explained by easily observable indicators of welfare like household characteristics and asset ownership.

In this program, updating poverty ranks by village heads provided a much quicker and less expensive alternative to a full PMT plus community-ranking and validation process, without compromising the targeting efficacy of the program and produced outcomes acceptable for the community. The results suggest that the performance of village heads compared to alternative methods may be particularly strong in remote areas with varying poverty levels. There, the village heads' familiarity with residents and local circumstances can help them distinguish among community members' relative welfare statuses. In these cases, a flexible targeting led by village heads may be successful at achieving pro-poor targeting objectives.

There are caveats about the applicability of these findings in other contexts. First, village heads only updated prior, community-supported poverty rankings in this program. This reduced the reliance on village heads for determination of eligibility and may have also improved community acceptability, since applicants may have perceived the updated rankings as a revision of a system they had already endorsed. Other populations without a comparable experience may view village head targeting as less legitimate. Second, the selection for the RMG program also relied on self-selection into the program by the neediest households. This may explain some of the targeting success of the program. Third, our analysis suggests that village heads hold a holistic impression of household welfare built on easily observable household and individual characteristics. This type of assessment may be less useful when targeting households with specific, less observable needs, such as the need for nutrition support.

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Appendix

Table A1: T-tests of RMG-eligible and RS Group Descriptive Statistics

Note: Yellow highlighting indicates that the variable was excluded during construction of composite z-scores to compare VHT against PMT, since these variables were used in construction of the PMT index.

Note: Variables marked "(inverted)" were not inverted in Table A1, but their individual z-scores were inverted when computing composite z-scores.

	RMG-eligible mean (N=1,146)	RMG-eligible SD	Random Sample mean (N=742)	Random Sample SD	Diff. (RMG-eligible – Random Sample)	P-val
Land and buildings ownership						
Size of agr. plots (thousand sqm)	19.3528	21.4625	19.6314	24.212	-0.2785	0.799
Size of res. plots (thousand sqm)	0.3287	0.6168	0.4269	0.7434	-0.0982***	0.003
Num. of buildings owned (res. and business)	1.0785	0.2969	1.1146	0.3805	-0.0360**	0.029
Household composition						
HH dependency ratio (inverted)	0.9138	0.6953	0.8761	0.7146	0.0377	0.258
Head of HH age (years)	41.5175	12.8011	43.6739	13.2874	-2.1564***	0.000
Head of HH education (years)	3.2818	2.9826	3.5957	3.3598	-0.3138**	0.039
Head of HH is female (inverted)	0.0925	0.2899	0.0472	0.2121	0.0453***	0.000
Head of HH is divorced (inverted)	0.0244	0.1545	0.0175	0.1313	0.0069	0.298
Head of HH is a widow (inverted)	0.0742	0.2622	0.0418	0.2002	0.0324***	0.002
Head of HH is married	0.8988	0.3018	0.9407	0.2363	-0.0419***	0.001
Head of HH was never married (inverted)	0.0026	0.0511	0	0	0.0026*	0.083
Head of HH ethnicity: Lao	0.1309	0.3374	0.1173	0.3219	0.0136	0.378
Head of HH ethnicity: Khmu	0.4319	0.4956	0.3733	0.484	0.0586**	0.011
Head of HH ethnicity: Katang (inverted)	0.1169	0.3215	0.1658	0.3721	-0.0488***	0.003
Head of HH ethnicity: Other (inverted)	0.3202	0.4668	0.3437	0.4753	-0.0234	0.292
Durables ownership						
Num. of vehicles (car, vans, etc.)	0.0253	0.1626	0.0499	0.2413	-0.0246**	0.015
Num. of motor cycles	0.7452	0.7451	0.8814	0.7789	-0.1362***	0.000
Num. of bicycles	0.0497	0.233	0.066	0.2933	-0.0163	0.202
Num. of refrigerators/freezers	0.0908	0.3272	0.1685	0.4346	-0.0777***	0.000
Num. of sewing machines	0.055	0.228	0.0714	0.2577	-0.0165	0.157

Num. of washing machines	0.0035	0.059	0.0216	0.1454	-0.0181***	0.001
Num. of electric rice cookers	0.0628	0.2567	0.097	0.3265	-0.0342**	0.016
Num. of steam rice cookers	1.4572	0.645	1.3989	0.6341	0.0583*	0.053
Num. of food processors	0.007	0.0833	0.0202	0.1501	-0.0132**	0.029
Num. of two- and four-wheel tractors	0.2373	0.4398	0.3369	0.4898	-0.0996***	0.000
Num. of agr. equipment	9.6152	5.909	10	6.3484	-0.3848	0.187
Num. of boats	0.0175	0.131	0.0377	0.1976	-0.0203**	0.014
Num. of fishing nets	0.548	0.8836	0.6402	1.0147	-0.0922**	0.043
Num. of rice mills	0.2784	0.4523	0.3113	0.4662	-0.033	0.129
Num. of TVs	0.3229	0.4807	0.4205	0.5334	-0.0976***	0.000
Num. of radios/VCD	0.1457	0.3928	0.1752	0.4078	-0.0295	0.120
Num. of telephones	0.1178	0.3609	0.1226	0.3482	-0.0048	0.771
Num. of mobile phones	1.4145	1.395	1.4569	1.3667	-0.0424	0.514
Num. of satellite discs/connections	0.3054	0.4608	0.3814	0.4861	-0.0760***	0.001
Num. of computers	0.0087	0.093	0.0216	0.1544	-0.0128**	0.042
Num. of air conditioners	0.0009	0.0295	0.0027	0.0519	-0.0018	0.384
Num. of jewelry	0.301	0.854	0.3383	0.9524	-0.0372	0.388
Num. of mosquito nets	2.9206	1.7012	3.0418	1.8323	-0.1212	0.149
Num. of solar panels	0.2286	0.4617	0.2776	0.5653	-0.0490**	0.049
Livestock ownership						
Num. of cows	1.1745	2.7296	1.973	3.896	-0.7985***	0.000
Num. of buffalos	0.5567	1.3927	0.9151	2.0999	-0.3584***	0.000
Num. of goats	0.5192	1.838	0.8518	2.2621	-0.3326***	0.001
Num. of pigss	1.9188	2.464	2.0526	2.7296	-0.1337	0.280
Num. of chickens	9.7164	14.5332	9.9447	14.0601	-0.2283	0.734
Num. of ducks	2.1195	4.4355	2.1132	4.4888	0.0063	0.976
Income						
Agriculture income	382.5096	1035.4527	406.5878	1085.7145	-24.0782	0.632
Livestock income	390.1721	916.5445	513.3494	1135.7117	-123.1773**	0.013
Fishes income	6.4066	26.6132	7.2247	29.5335	-0.8181	0.541
Forest income	159.6157	307.38	137.9027	323.628	21.713	0.147

Handicraft income	94.7048	340.7649	89.1626	360.8131	5.5421	0.739
Services income	30.8876	181.66	49.3024	232.1116	-18.4148*	0.068
Salary income	435.9056	1741.3517	809.0677	2522.6435	-373.1622***	0.000
Extra income	150.4058	520.9682	114.4544	448.0776	35.9515	0.111
Other income	114.9503	380.2719	102.258	360.7227	12.6924	0.465
Total income	1933.775	2951.829	2410.1417	3614.1872	-476.3667***	0.003
Total income per HH member (USD PPP)	381.919	620.3777	480.733	789.1612	-98.8140***	0.004
Housing conditions						
Dwelling: num. of rooms	1.9171	1.1149	2.0782	1.1176	-0.1611***	0.002
Dwelling walls: brick	0.0654	0.2474	0.0755	0.2643	-0.01	0.409
Dwelling walls: concrete	0.0637	0.2443	0.0903	0.2868	-0.0266**	0.037
Dwelling walls: wood	0.5663	0.4958	0.624	0.4847	-0.0577**	0.012
Dwelling walls: bamboo (inverted)	0.2862	0.4522	0.1873	0.3904	0.0989***	0.000
Dwelling roof: concrete	0.0052	0.0722	0.0013	0.0367	0.0039	0.123
Dwelling roof: wood	0.0271	0.1623	0.0216	0.1454	0.0055	0.444
Dwelling roof: metal (inverted)	0.5977	0.4906	0.6173	0.4864	-0.0195	0.396
Dwelling roof: tile	0.3028	0.4597	0.3167	0.4655	-0.0139	0.524
Dwelling roof: grass (inverted)	0.0611	0.2396	0.0418	0.2002	0.0193*	0.059
Dwelling floor: tile	0.1213	0.3266	0.1402	0.3474	-0.0189	0.238
Dwelling floor: concrete	0.0733	0.2607	0.0768	0.2665	-0.0035	0.777
Dwelling floor: wood (inverted)	0.5672	0.4957	0.6011	0.49	-0.0339	0.144
Dwelling floor: bamboo (inverted)	0.0864	0.2811	0.0606	0.2388	0.0257**	0.033
Dwelling floor: earth/clay (inverted)	0.1518	0.359	0.1213	0.3267	0.0305*	0.057
Rainy season water: piped water	0.178	0.3827	0.1752	0.3804	0.0028	0.876
Rainy season water: protected well	0.5332	0.4991	0.4704	0.4995	0.0628***	0.008
Rainy season water: unprotected well (inverted)	0.0515	0.2211	0.0687	0.2532	-0.0172	0.129
Rainy season water: river/lake (inverted)	0.1344	0.3412	0.1132	0.3171	0.0212	0.169
Dry season water: piped water	0.1806	0.3849	0.1792	0.3838	0.0014	0.939
Dry season water: protected well	0.5663	0.4958	0.5162	0.5001	0.0501**	0.033

Dry season water: unprotected well (inverted)	0.0812	0.2732	0.1065	0.3086	-0.0253*	0.069
Dry season water: river/lake (inverted)	0.1571	0.364	0.1482	0.3556	0.0088	0.602
Toilet: flush	0.4066	0.4914	0.4003	0.4903	0.0064	0.783
Toilet: no facility (inverted)	0.4171	0.4933	0.4097	0.4921	0.0074	0.750
Toilet: shared (inverted)	0.3709	0.4832	0.3693	0.4829	0.0016	0.945
Kitchen type: inside the house (inverted)	0.5061	0.5002	0.4394	0.4966	0.0668***	0.005
Kitchen type: outside roofed	0.4738	0.4995	0.5404	0.4987	-0.0666***	0.005
Kitchen type: outside unroofed (inverted)	0.014	0.1174	0.0148	0.1209	-0.0009	0.878
Cooking fuel: wood (inverted)	0.993	0.0833	0.9744	0.1581	0.0186***	0.003
Cooking fuel: charcoal	0.007	0.0833	0.0256	0.1581	-0.0186***	0.003
Lighting source: electric network	0.3839	0.4866	0.4623	0.4989	-0.0783***	0.001
Lighting source: generator (inverted)	0.0271	0.1623	0.0202	0.1408	0.0068	0.332
Lighting source: battery (inverted)	0.0183	0.1342	0.0243	0.154	-0.0059	0.390
Lighting source: kerosene lamp (inverted)	0.062	0.2412	0.0553	0.2286	0.0067	0.543
Lighting source: solar panel (inverted)	0.1894	0.392	0.2102	0.4078	-0.0209	0.270
Nutrition						
Num. of balls of glutinous rice for women (prior day)	8.8194	8.0422	8.6482	8.1434	0.1711	0.654
Num. of balls of glutinous rice for kids (prior day)	1.4508	3.2564	1.5086	3.3957	-0.0579	0.713
Num. of bowls of ordinary rice for women (prior day, inverted)	3.4171	2.8494	3.2884	2.678	0.1287	0.320
Daily num. of bowls of ordinary rice for kids (prior day, inverted)	0.2203	0.8912	0.1157	0.608	0.1046***	0.002
Num. of days woman eats meat (weekly)	2.7635	2.2208	2.7102	2.1872	0.0533	0.607
Num. of days woman eats eggs (weekly)	0.5445	1.1778	0.5013	1.0882	0.0432	0.415
Num. of days woman eats dairy (weekly)	0.1091	0.6484	0.0768	0.5125	0.0323	0.230
Num. of days child eats meat (weekly)	0.9223	1.8741	0.746	1.6267	0.1764**	0.030
Num. of days child eats eggs (weekly)	0.2757	0.9997	0.219	0.7868	0.0567	0.170
Num. of days child eats dairy (weekly)	0.0881	0.6897	0.062	0.5705	0.0261	0.371
Kg of meat per HH member (weekly)	0.2385	0.2637	0.2367	0.2939	0.0018	0.892
Kg of fish per HH member (weekly)	0.2021	0.2522	0.2036	0.2487	-0.0015	0.899
Kg of vegetables per HH member (weekly)	0.907	1.0112	0.827	0.8545	0.0801*	0.065

Kg of fruits per HH member (weekly)	0.3822	0.5745	0.3181	0.4934	0.0641***	0.010
Exposure to Shocks						
Family death shock (inverted)	0.1239	0.3296	0.124	0.3298	-0.0001	0.996
Illness shock (inverted)	0.5646	0.496	0.5593	0.4968	0.0053	0.822
Business or unemployment shock (inverted)	0.0654	0.2474	0.0512	0.2206	0.0142	0.192
Natural disaster shock (inverted)	0.178	0.3827	0.1941	0.3957	-0.0161	0.383
Crop loss shock (inverted)	0.4171	0.4933	0.4461	0.4974	-0.029	0.215
Robbery shock (inverted)	0.6614	0.4734	0.6752	0.4686	-0.0138	0.535
Woman characteristics						
Woman age (years)	33.0995	10.5313	33.8491	10.2717	-0.7496	0.125
Woman education (years)	2.4485	2.7485	2.6361	3.3249	-0.1876	0.201
Woman is divorced (inverted)	0.0288	0.1673	0.0189	0.1362	0.0099	0.158
Woman is a widow (inverted)	0.0567	0.2314	0.0202	0.1408	0.0365***	0.000
Woman is married	0.8743	0.3316	0.9205	0.2707	-0.0461***	0.001
Woman was never married (inverted)	0.0401	0.1964	0.0404	0.1971	-0.0003	0.975
Woman ethnicity: Lao	0.1283	0.3345	0.1186	0.3235	0.0097	0.531
Woman ethnicity: Khmu	0.4319	0.4956	0.372	0.4837	0.0600***	0.009
Woman ethnicity: Katang (inverted)	0.1134	0.3173	0.1617	0.3684	-0.0483***	0.003
Woman ethnicity: Other (inverted)	0.3264	0.4691	0.3477	0.4766	-0.0214	0.339
Woman works on HH farm (inverted)	3.5855	2.8454	3.1927	2.8634	0.3928***	0.004
Woman works in HH business	0.1667	0.9789	0.283	1.3187	-0.1164**	0.039
Woman works in non-HH business	0.9145	2.0791	0.628	1.8519	0.2865***	0.002
Connections with village head						
Woman often or sometime had conversations with the village head in the past month	0.7033	1.1038	0.4946	0.9744	0.2087***	0.000
Someone in HH is a close friend/relative with the village head	0.7042	0.4566	0.6644	0.4725	0.0398*	0.071

* p<0.1 ** p<0.05 *** p<0.01

Table A2: Variable Weights for PMT Index

PMT Variables
Employment and Income
Someone in the HH owns a business
Someone in the HH is an employee
Someone in the HH is self-employed
HH has non-labor income (rent, remittances, pension)
HH Members 15 to 64 years old
None
1 person
2 persons
3 persons
4 persons
5 or more persons
HH members 0-14 years old and elderly over 64 years
None
1 person
2 persons or more
Highest education completed by hh members
Vocational school or university
Secondary school or lower
Housing Conditions
Roof material: concrete or wood
Wall material: brick or concrete
Floor material: marble, ceramic, or tiles
Drinking water: pipe water or bottled water
Toilet ownership: own toilet
Asset Ownership
Washing machine
Refrigerator
Air conditioner
TV
Mobile phone
Telephone
Computer
Car
Motorcycle
Bicycle
Village Public Services
Access to permanent/daily market
Access to periodical market at least twice a week
Access to lower secondary school
Access to upper secondary school
Access to road
Accessible road during wet season

Table A3: Village heads vs PMT – Ranked Sample of 1,245 Households

RMG-eligible	PMT below 64		Total
	No	Yes	
No	193 (16%)	294 (24%)	487 (39%)
Yes	266 (21%)	492 (40%)	758 (61%)
Total	459 (37%)	786 (63%)	1,245 (100%)

Table A3: T-Test comparison of village head and PMT targeting methods – Across the full sample

	RMG-eligible obs.	Random Sample obs.	RMG-eligible mean	Random Sample mean	Diff. (RMG-eligible – Random Sample)	PMT poor obs.	PMT nonpoor obs.	PMT poor mean	PMT nonpoor mean	Diff. (PMT poor - nonpoor)
Household composition	1146	742	-0.0151	0.0233	-0.0384**	1187	701	-0.0039	0.0066	-0.0106
Exposure to shocks	1146	742	0.0039	-0.0059	0.0098	1187	701	-0.0047	0.0080	-0.0128
Land and buildings ownership	1146	742	-0.0312	0.0482	-0.0794**	1187	701	-0.0259	0.0438	-0.0696*
Nutrition	1146	742	0.0097	-0.0149	0.0246*	1187	701	-0.0423	0.0716	-0.1140***
Livestock ownership	1146	742	-0.0449	0.0693	-0.1142***	1187	701	-0.0535	0.0906	-0.1442***
Housing conditions	1146	742	-0.0207	0.0320	-0.0527***	1187	701	-0.0640	0.1084	-0.1725***
Durables ownership	1146	742	-0.0345	0.0533	-0.0879***	1187	701	-0.0646	0.1093	-0.1739***
Total income per HH member	1146	742	-0.0560	0.0865	-0.1426***	1187	701	-0.3049	0.5164	-0.8213***

Note: Variables are rendered as composite z-scores, computed by excluding variables used in the creation of the PMT index, and by estimating means and standard deviations for the whole sample of 1,888 observations.

* p<0.1 ** p<0.05 *** p<0.01

Table A4: T-test comparison of village head and PMT targeting methods – Grouped by village

	RMG-eligible obs.	Random Sample obs.	RMG-eligible mean	Random Sample mean	Diff. (RMG-eligible – Random Sample)	PMT poor obs.	PMT nonpoor obs.	PMT poor mean	PMT nonpoor mean	Diff. (PMT poor - nonpoor)
Household composition	1146	742	-0.0231	0.0357	-0.0589***	1187	701	0.0149	-0.0252	0.0400***
Exposure to shocks	1146	742	0.0024	-0.0037	0.006	1187	701	-0.0115	0.0195	-0.031
Land and buildings ownership	1146	742	-0.0178	0.0275	-0.0453	1187	701	-0.0213	0.0361	-0.0574
Woman characteristics	1146	742	-0.0134	0.0207	-0.0342***	1187	701	-0.0079	0.0133	-0.0211*
Nutrition	1146	742	0.0061	-0.0095	0.0156	1187	701	-0.0213	0.0360	-0.0573***
Livestock ownership	1146	742	-0.0548	0.0846	-0.1394***	1187	701	-0.0348	0.0589	-0.0936***
Housing conditions	1146	742	-0.0156	0.0240	-0.0396***	1187	701	-0.0151	0.0256	-0.0408***
Durables ownership	1146	742	-0.0283	0.0436	-0.0719***	1187	701	-0.0230	0.0390	-0.0620***
Total income per HH member	1146	742	-0.0849	0.1311	-0.2160***	1187	701	-0.2011	0.3406	-0.5417***

Note: Variables are rendered as composite z-scores, computed by excluding variables used in the creation of the PMT index, and by estimating means and standard deviations for each village in the sample of 1,888 observations.
* p<0.1 ** p<0.05 *** p<0.01

Table A5: T-tests of composite z-cores for RMG selection

	RMG-eligible obs.	Random Sample obs.	RMG-eligible mean		Diff. (RMG-eligible –	P-val

				Random Sample mean	Random Sample)		Bonferroni corrected p-val
Land and buildings ownership	1146	742	-0.0312	0.0482	-0.0794	0.027	0.213
Household composition	1146	742	-0.0151	0.0233	-0.0384	0.041	0.326
Durables ownership	1146	742	-0.0345	0.0533	-0.0879***	0.000	0.000
Livestock ownership	1146	742	-0.0449	0.0693	-0.1142***	0.000	0.001
Total income per HH member (USD PPP)	1146	742	381.919	480.733	-98.8140**	0.004	0.032
Housing conditions	1146	742	-0.0207	0.032	-0.0527***	0.000	0.002
Nutrition	1146	742	0.0097	-0.0149	0.0246	0.084	0.669
Exposure to shocks	1146	742	0.0039	-0.0059	0.0098	0.666	1.000

RMG-eligible = 1146 observations. Random Sample = 742 observations. All household characteristics are shared as composite z-scores, except for total income per HH member. Variables included are those used in comparisons of RMG and PMT scores.

Construction of individual and composite z-scores

There are two challenges when analyzing a large number of variables. First, the number of variables and outcomes of t-tests can make it difficult to interpret results. Second, analysis of multiple outcomes increases the risk of Type I error unless the significance tests are adjusted appropriately. Following Kling et al. (2007), we compute composite z-scores as means of individual z-scores for all variables in each group of variables, while inverting variables assumed to be negatively correlated with welfare.

We employ the following strategies:

- We identify a set of primary outcomes under each of the following groups, noted in Table A1:
  - Land and buildings ownership;
  - Household composition;
  - Durables ownership;
  - Livestock ownership;
  - Income;
  - Housing conditions;
  - Nutrition;
  - Exposure to shocks;
  - Woman characteristics
- For income, we use aggregate income per household member since it is better at capturing the underlying notion of welfare than could be achieved through a mean z-score of different types of income. For all other categories of outcomes, we compute composite z-scores through a uniform procedure:
  - Calculate the z-score of all variables by subtracting the mean and dividing by the standard deviation;
  - Convert all outcomes so that the signs of all variables in a category go in the same direction of being positively correlated with improved welfare;
  - In Table A1, all variables negatively correlated with welfare are shown as "inverted," meaning that their z-scores would be inverted for the composite z-score calculation, though they are not inverted for descriptive statistics or individual z-scores;
  - Compute composite z-scores for 8 (eight) categories by taking an average of the z-scores of all variables in a given category.
- In the computation of composite z-scores used to compare VHT and PMT targeting methods in Figures 6 and 7, and Tables A3 and A4, we exclude variables used in the construction of the PMT index. Hence, the computation procedure is the same as above, but the following variables are excluded when calculating the composite z-scores for their categories:
  - Land and buildings ownership:
    - Number of buildings owned (residential and business)
  - Household characteristics:
    - HH dependency ratio
    - Head of household education (years)
  - Durables ownership:
    - Num. vehicle (car, van...)
    - Num. many motorcycle
    - Num. many bicycle
    - Num. refrigerator/freezer

        - Num. washing machine
        - Num. television
        - Num. telephone
        - Num. mobile phone
        - Num. computer
        - Num. air conditioner
    - Housing conditions:
        - Dwelling walls: brick
        - Dwelling walls: concrete
        - Dwelling roof: concrete
        - Dwelling roof: wood
        - Dwelling floor: tile
        - Dry season water: piped water
        - Dry season water: protected well
        - Dry season water: unprotected well (inverted)
        - Dry season water: river/lake (inverted)
        - Toilet: flush
        - Toilet: no facility (inverted)
        - Toilet: shared (inverted)
    - Woman characteristics:
        - Woman education (years)
- In Figure 7 and Table A4, we compute individual variables' z-scores by subtracting village-level means and dividing by village-level standard deviations. Composite z-scores are thus averages of village-based z-scores of variables in each category.

Importance of vars: Village heads ranking by RMG priority

Woman works in non-hh business	1.0000
Kitchen type: outside unroofed	0.7218
Dwelling walls: concrete	0.6918
Num. of days woman eats dairy (weekly)	0.5555
Services income	0.5455
Woman was never married	0.5240
Woman's conversations with village head	0.4975
Dwelling floor: tile	0.4411
Dry season water: unprotected well	0.4381
Head of hh is a widow	0.4305
Lighting source: kerosene lamp	0.4297
Fishes income	0.4256
Lighting source: solar panel	0.4143
Dwelling roof: grass	0.3987
Dwelling walls: brick	0.3832
Dwelling roof: concrete	0.3762
Family death shock	0.3704
Lighting source: battery	0.3699
Business or unemployment shock	0.3615
Head of hh is female	0.3569
Num. of days kids eat eggs (weekly)	0.3565
Num. of days kids eat dairy (weekly)	0.3561
Kitchen type: outside roofed	0.3555
Rainy season water: unprotected well	0.3549
Dry season water: piped water	0.3539

Woman is a widow	0.3487
Daily num. of balls of ord. rice for kids	0.3479
Toilet: no facility	0.3446
Rainy season water: piped water	0.3396
Num. of goats	0.3383
Head of hh was never married	0.3344
Dry season water: river/lake	0.3315
Num. of buildings owned	0.3283
Dwelling floor: earth/clay	0.3270
Cooking fuel: wood	0.3268
Natural disaster shock	0.3251
Lighting source: generator	0.3249
Woman ethnicity: Katang	0.3220
Num. of days woman eats eggs (weekly)	0.3201
Woman works in hh business	0.3160
Dwelling roof: tile	0.3147
Salary income	0.3145
Num. of jewelry	0.3139
Head of hh age (years)	0.3116
Toilet: flush	0.3091
Woman ethnicity: Lao	0.3082
Lighting source: electric network	0.3077
Num. of sewing machines	0.3063
Woman ethnicity: Other	0.3052
Num. of days kids eat meat (weekly)	0.3019
Num. of days woman eats meat (weekly)	0.2992
Woman works on hh farm	0.2989
Total income per hh member	0.2977

Rainy season water: protected well	0.2958
Head of hh ethnicity: Khmu	0.2935
Toilet: shared	0.2895
Dwelling walls: bamboo	0.2892
Kg of veggies per hh member (weekly)	0.2861
Kg of meat per hh member (weekly)	0.2858
Dwelling floor: wood	0.2857
Crop loss shock	0.2850
Dwelling walls: wood	0.2848
Daily num. of balls of ord. rice for women	0.2842
Cooking fuel: charcoal	0.2839
Illness shock	0.2830
Daily num. of balls of glut. rice for kids	0.2825
Kg of fruits per hh member (weekly)	0.2813
Head of hh ethnicity: Katang	0.2811
Kitchen type: inside the house	0.2795
Extra income	0.2770
Num. of computers	0.2747
Robbery shock	0.2738
Num. of solar panels	0.2732
Kg of fish per hh member (weekly)	0.2731
Dry season water: protected well	0.2722
Num. of telephones	0.2721
Dwelling: num. of rooms	0.2715
Total income	0.2700
Head of hh ethnicity: Lao	0.2684
Handicraft income	0.2680
Rainy season water: river/lake	0.2665

Head of hh ethnicity: Other	0.2657
Woman ethnicity: Khmu	0.2648
Head of hh education (years)	0.2643
Dwelling floor: concrete	0.2637
Someone in hh is a friend/relative with village head	0.2596
Agr. income	0.2566
Daily num. of balls of glut. rice for women	0.2551
Head of hh is divorced	0.2549
Woman age (years)	0.2507
Other income	0.2494
Dwelling floor: bamboo	0.2492
Num. of cows	0.2455
Num. of ducks	0.2441
Dwelling roof: metal	0.2410
Woman is divorced	0.2374
Num. of buffalos	0.2320
Num. of washing machines	0.2319
Woman education (years)	0.2285
Forest income	0.2279
Woman is married	0.2251
Num. of TVs	0.2221
Livestock income	0.2205
Num. of satellite discs/connections	0.2158
Num. of radios/vcd	0.2154
Num. of rice mills	0.2134
Num. of food processors	0.2087
HH dependency ratio	0.2085
Num. of chickens	0.2082

Head of hh is married	0.2067
Dwelling roof: wood	0.2028
Num. of pigss	0.1946
Num. of mosquito nets	0.1870
Num. of fishing nets	0.1747
Num. of air conditioners	0.1720
Num. of mobile phones	0.1715
Num. of boats	0.1696
Num. of refrigerators/freezers	0.1620
Num. of agr. equipments	0.1391
Num. of two- and four-wheel tractors	0.1359
Num. of motor cycles	0.1354
Num. of electric rice cookers	0.1334
Num. of vehicles (car, vans, etc.)	0.1330
Num. of steam rice cookers	0.1204
Num. of bicycles	0.1049
Size of res. plots (thousand sqm)	0.0852
Size of agr. plots (thousand sqm)	0.0627

Importance of vars: Village heads ranking by land

Dwelling walls: bamboo	1.0000
Dwelling: num. of rooms	0.8370
Dwelling walls: concrete	0.8223
Services income	0.8071
Total income	0.7809
Num. of cows	0.7534
Head of hh is a widow	0.7211
Dwelling floor: earth/clay	0.6908

Dwelling roof: tile	0.6863
Head of hh age (years)	0.6840
Woman works in hh business	0.6806
Dwelling floor: bamboo	0.6672
Num. of satellite discs/connections	0.6315
Dwelling floor: concrete	0.6170
Head of hh was never married	0.6102
Family death shock	0.6090
Head of hh is female	0.5884
Num. of buffalos	0.5786
Num. of days kids eat eggs (weekly)	0.5781
Dwelling floor: tile	0.5667
Woman ethnicity: Lao	0.5510
Dry season water: unprotected well	0.5469
Num. of mobile phones	0.5369
Lighting source: generator	0.5282
Cooking fuel: wood	0.5274
Rainy season water: river/lake	0.5260
Num. of days kids eat meat (weekly)	0.5000
Total income per hh member	0.4987
Kitchen type: outside roofed	0.4969
Woman is a widow	0.4947
Num. of mosquito nets	0.4938
Daily num. of balls of ord. rice for kids	0.4909
Dry season water: piped water	0.4894
Num. of rice mills	0.4892
Lighting source: solar panel	0.4821
Lighting source: kerosene lamp	0.4805

Head of hh ethnicity: Lao	0.4799
Woman was never married	0.4797
Kitchen type: outside unroofed	0.4779
Crop loss shock	0.4775
Woman's conversations with village head	0.4767
Natural disaster shock	0.4739
Num. of days woman eats meat (weekly)	0.4692
Business or unemployment shock	0.4681
Kitchen type: inside the house	0.4593
Dry season water: river/lake	0.4590
Num. of days kids eat dairy (weekly)	0.4579
Num. of TVs	0.4574
Dwelling walls: brick	0.4565
Toilet: flush	0.4551
Dry season water: protected well	0.4531
Lighting source: electric network	0.4514
Rainy season water: piped water	0.4499
Num. of computers	0.4467
Toilet: no facility	0.4458
Woman works in non-hh business	0.4425
Someone in hh is a friend/relative with village head	0.4425
Num. of days woman eats dairy (weekly)	0.4419
Dwelling roof: wood	0.4403
Daily num. of balls of glut. rice for kids	0.4398
Daily num. of balls of ord. rice for women	0.4392
Robbery shock	0.4358
Num. of ducks	0.4339
Kg of fruits per hh member (weekly)	0.4298

Rainy season water: protected well	0.4268
Num. of chickens	0.4255
Salary income	0.4244
Livestock income	0.4242
Kg of veggies per hh member (weekly)	0.4238
Toilet: shared	0.4218
Lighting source: battery	0.4188
Dwelling walls: wood	0.4185
Other income	0.4175
Kg of fish per hh member (weekly)	0.4171
Illness shock	0.4150
Agr. income	0.4132
Kg of meat per hh member (weekly)	0.4119
Num. of days woman eats eggs (weekly)	0.4085
Daily num. of balls of glut. rice for women	0.4081
Woman ethnicity: Other	0.4062
Dwelling floor: wood	0.4008
Woman ethnicity: Khmu	0.4004
Num. of buildings owned	0.3969
Head of hh is divorced	0.3962
Woman age (years)	0.3948
Woman education (years)	0.3874
Dwelling roof: grass	0.3811
Handicraft income	0.3792
Woman is divorced	0.3744
Dwelling roof: metal	0.3711
Woman works on hh farm	0.3704
Fishes income	0.3679

Head of hh education (years)	0.3659
Extra income	0.3625
Head of hh ethnicity: Katang	0.3610
Head of hh ethnicity: Other	0.3608
Head of hh ethnicity: Khmu	0.3578
Woman is married	0.3560
Rainy season water: unprotected well	0.3546
Num. of goats	0.3424
Woman ethnicity: Katang	0.3386
Head of hh is married	0.3375
Forest income	0.3323
Num. of telephones	0.3304
Cooking fuel: charcoal	0.3215
HH dependency ratio	0.3186
Num. of radios/vcd	0.3164
Num. of jewelry	0.3115
Num. of bicycles	0.3063
Num. of solar panels	0.3060
Num. of pigss	0.3059
Num. of motor cycles	0.2988
Num. of refrigerators/freezers	0.2928
Num. of two- and four-wheel tractors	0.2913
Dwelling roof: concrete	0.2858
Num. of boats	0.2667
Num. of agr. equipments	0.2454
Num. of fishing nets	0.2410
Num. of electric rice cookers	0.2291
Num. of food processors	0.2195

Num. of sewing machines	0.2171
Num. of vehicles (car, vans, etc.)	0.1867
Size of agr. plots (thousand sqm)	0.1704
Num. of steam rice cookers	0.1670
Size of res. plots (thousand sqm)	0.1662
Num. of washing machines	0.1430
Num. of air conditioners	0.0760

Importance of vars: Village heads ranking by hunger

Dwelling walls: concrete	1.0000
Dwelling floor: tile	0.9515
Dwelling: num. of rooms	0.7716
Num. of motor cycles	0.7146
Total income	0.6791
Dwelling walls: bamboo	0.6732
Woman works in hh business	0.6621
Head of hh is female	0.6372
Num. of buffalos	0.6142
Dwelling roof: tile	0.6003
Head of hh ethnicity: Katang	0.5282
Num. of mobile phones	0.5218
Dwelling floor: concrete	0.5099
Rainy season water: unprotected well	0.5055
Services income	0.4988
Toilet: no facility	0.4792
Head of hh is a widow	0.4777
Woman is a widow	0.4772
Dwelling floor: earth/clay	0.4763

Dwelling roof: grass	0.4707
Total income per hh member	0.4702
Lighting source: kerosene lamp	0.4684
Dry season water: unprotected well	0.4680
Num. of refrigerators/freezers	0.4678
Kitchen type: inside the house	0.4620
Daily num. of balls of ord. rice for kids	0.4541
Num. of cows	0.4441
Num. of buildings owned	0.4438
Kitchen type: outside unroofed	0.4417
Kitchen type: outside roofed	0.4413
Livestock income	0.4412
Lighting source: battery	0.4354
Business or unemployment shock	0.4239
Dwelling floor: bamboo	0.4231
Num. of TVs	0.4214
Dry season water: protected well	0.4199
Toilet: flush	0.3972
Fishes income	0.3971
Dwelling walls: brick	0.3963
Lighting source: generator	0.3942
Lighting source: solar panel	0.3939
Family death shock	0.3935
Num. of days kids eat eggs (weekly)	0.3928
Rainy season water: protected well	0.3914
Daily num. of balls of ord. rice for women	0.3897
Num. of days woman eats meat (weekly)	0.3851
Lighting source: electric network	0.3845

Toilet: shared	0.3839
Num. of days woman eats dairy (weekly)	0.3827
Rainy season water: piped water	0.3806
Woman is divorced	0.3798
Woman education (years)	0.3782
Woman ethnicity: Lao	0.3778
Robbery shock	0.3751
Num. of rice mills	0.3723
Someone in hh is a friend/relative with village head	0.3718
Kg of fruits per hh member (weekly)	0.3683
Woman's conversations with village head	0.3681
Woman was never married	0.3668
Illness shock	0.3646
Natural disaster shock	0.3610
Dry season water: piped water	0.3609
Head of hh ethnicity: Lao	0.3571
Head of hh is divorced	0.3557
Num. of satellite discs/connections	0.3549
Kg of veggies per hh member (weekly)	0.3534
Woman ethnicity: Katang	0.3533
Dry season water: river/lake	0.3532
Num. of days kids eat meat (weekly)	0.3528
Crop loss shock	0.3519
Num. of chickens	0.3497
Cooking fuel: wood	0.3484
Rainy season water: river/lake	0.3472
Woman works on hh farm	0.3467
Kg of fish per hh member (weekly)	0.3460

Daily num. of balls of glut. rice for women	0.3447
Num. of mosquito nets	0.3439
Woman ethnicity: Other	0.3405
Kg of meat per hh member (weekly)	0.3403
Dwelling floor: wood	0.3393
Num. of days woman eats eggs (weekly)	0.3379
Daily num. of balls of glut. rice for kids	0.3365
Head of hh education (years)	0.3319
Head of hh ethnicity: Khmu	0.3296
Dwelling walls: wood	0.3290
Woman ethnicity: Khmu	0.3268
Woman works in non-hh business	0.3240
Agr. income	0.3203
Head of hh was never married	0.3201
Handicraft income	0.3183
Num. of sewing machines	0.3109
Extra income	0.3071
Head of hh ethnicity: Other	0.3053
Num. of jewelry	0.2993
Salary income	0.2979
Woman is married	0.2957
Woman age (years)	0.2932
Head of hh is married	0.2905
Other income	0.2899
Head of hh age (years)	0.2878
Dwelling roof: metal	0.2846
Num. of pigss	0.2796
Num. of goats	0.2701

Forest income	0.2689
Num. of ducks	0.2685
Num. of days kids eat dairy (weekly)	0.2653
Num. of solar panels	0.2541
HH dependency ratio	0.2532
Cooking fuel: charcoal	0.2510
Num. of telephones	0.2484
Num. of vehicles (car, vans, etc.)	0.2388
Num. of boats	0.2347
Num. of radios/vcd	0.2324
Num. of fishing nets	0.2307
Num. of two- and four-wheel tractors	0.2216
Dwelling roof: wood	0.2153
Num. of bicycles	0.2066
Num. of agr. equipments	0.2030
Num. of food processors	0.1928
Num. of electric rice cookers	0.1919
Num. of computers	0.1732
Dwelling roof: concrete	0.1640
Num. of steam rice cookers	0.1598
Size of agr. plots (thousand sqm)	0.1547
Size of res. plots (thousand sqm)	0.1530
Num. of washing machines	0.1488
Num. of air conditioners	0.1318

Importance of vars: Village heads ranking by need

Dwelling: num. of rooms	1.0000
Services income	0.9838

Head of hh is female	0.9774
Num. of mobile phones	0.8470
Woman works in hh business	0.7672
Dwelling walls: concrete	0.7033
Dwelling walls: bamboo	0.6860
Total income	0.6722
Woman is a widow	0.6459
Dwelling roof: tile	0.6241
Head of hh is a widow	0.6015
Lighting source: kerosene lamp	0.5926
Dry season water: unprotected well	0.5660
Num. of motor cycles	0.5571
Dwelling floor: tile	0.5508
Num. of days kids eat meat (weekly)	0.5202
Num. of days kids eat dairy (weekly)	0.5187
Kitchen type: inside the house	0.5035
Livestock income	0.4971
Dwelling roof: grass	0.4965
Daily num. of balls of ord. rice for kids	0.4933
Toilet: no facility	0.4900
Kitchen type: outside roofed	0.4886
Num. of buildings owned	0.4823
Num. of buffalos	0.4807
Lighting source: generator	0.4652
Business or unemployment shock	0.4580
Num. of cows	0.4559
Total income per hh member	0.4530
Lighting source: battery	0.4505

Lighting source: solar panel	0.4494
Dwelling floor: concrete	0.4437
Kg of fish per hh member (weekly)	0.4431
Num. of days kids eat eggs (weekly)	0.4424
Dwelling floor: bamboo	0.4421
Kitchen type: outside unroofed	0.4418
Cooking fuel: wood	0.4339
Dwelling floor: earth/clay	0.4311
Num. of rice mills	0.4292
Family death shock	0.4283
Woman works in non-hh business	0.4189
Woman was never married	0.4182
Num. of refrigerators/freezers	0.4153
Dry season water: piped water	0.4148
Head of hh ethnicity: Katang	0.4130
Dry season water: protected well	0.4114
Toilet: flush	0.4083
Toilet: shared	0.4066
Head of hh is divorced	0.4013
Woman ethnicity: Other	0.3978
Fishes income	0.3969
Daily num. of balls of glut. rice for kids	0.3958
Head of hh ethnicity: Lao	0.3876
Rainy season water: piped water	0.3874
Head of hh ethnicity: Other	0.3872
Rainy season water: unprotected well	0.3858
Natural disaster shock	0.3817
Kg of veggies per hh member (weekly)	0.3811

Salary income	0.3805
Woman's conversations with village head	0.3778
Num. of satellite discs/connections	0.3775
Woman ethnicity: Lao	0.3744
Num. of days woman eats dairy (weekly)	0.3729
Num. of days woman eats eggs (weekly)	0.3711
Rainy season water: river/lake	0.3710
Kg of meat per hh member (weekly)	0.3702
Num. of days woman eats meat (weekly)	0.3698
Kg of fruits per hh member (weekly)	0.3666
Illness shock	0.3645
Robbery shock	0.3643
Daily num. of balls of glut. rice for women	0.3632
Extra income	0.3627
Someone in hh is a friend/relative with village head	0.3624
Other income	0.3618
Dwelling floor: wood	0.3608
Rainy season water: protected well	0.3591
Dry season water: river/lake	0.3570
Woman is divorced	0.3558
Daily num. of balls of ord. rice for women	0.3556
Dwelling walls: brick	0.3521
Lighting source: electric network	0.3510
Dwelling roof: wood	0.3510
Crop loss shock	0.3483
Dwelling walls: wood	0.3474
Num. of TVs	0.3452
Num. of mosquito nets	0.3441

Num. of chickens	0.3389
Head of hh ethnicity: Khmu	0.3378
Woman ethnicity: Katang	0.3358
Woman education (years)	0.3292
Agr. income	0.3260
Dwelling roof: metal	0.3256
Num. of ducks	0.3252
Num. of pigss	0.3247
Woman works on hh farm	0.3234
Handicraft income	0.3220
Woman age (years)	0.3167
Head of hh education (years)	0.3143
Num. of goats	0.3099
Head of hh age (years)	0.3098
Woman ethnicity: Khmu	0.3060
Forest income	0.3047
Head of hh is married	0.3014
Woman is married	0.2927
HH dependency ratio	0.2851
Num. of sewing machines	0.2806
Cooking fuel: charcoal	0.2797
Num. of telephones	0.2779
Num. of air conditioners	0.2762
Num. of jewelry	0.2650
Num. of solar panels	0.2641
Num. of vehicles (car, vans, etc.)	0.2447
Num. of two- and four-wheel tractors	0.2382
Num. of radios/vcd	0.2298

Num. of electric rice cookers	0.2189
Head of hh was never married	0.2178
Num. of boats	0.2130
Num. of fishing nets	0.1945
Num. of agr. equipments	0.1837
Num. of food processors	0.1681
Num. of steam rice cookers	0.1552
Num. of washing machines	0.1524
Num. of computers	0.1514
Dwelling roof: concrete	0.1501
Num. of bicycles	0.1399
Size of agr. plots (thousand sqm)	0.1173
Size of res. plots (thousand sqm)	0.1170