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Abstract

Targeting of national anti-poverty programs in low-income countries commonly relies on statistical procedures involving household-level survey data, while small-scale poverty-alleviation programs often employ so-called community-based targeting, where village communities themselves identify program beneficiaries. Combining data from community-based targeting exercises in north-western Burkina Faso with household-level survey data, we compare the targeting accuracy of community-based targeting with several statistical procedures when the program's purpose is to target consumption-poor households. We find that the community-based assessment targets a similar share of consumption-poor households as the best-performing statistical procedures which are not calibrated with household-level consumption data. Community-based targeting performs relatively better in urban than in rural areas and is not at a disadvantage in larger or more heterogeneous communities. In a cost-benefit analysis we find that in our sub-Saharan African context community-based targeting is far more cost-effective than any statistical procedure for common amounts of welfare program benefits.

Keywords: *Targeting, Community-based Targeting, Welfare Programs, Poverty, Community Wealth Rankings, Proxy-means Testing*

JEL Codes: G22, I13, I38, O15

1 Introduction

Poverty reduction programs designed to directly improve the well-being of the poor have become increasingly popular around the global South (Coady et al., 2004a). When a program's purpose is to maximize poverty reduction under a limited budget, its success depends on the program's individual welfare effects as well as on the accuracy of the underlying targeting method (Ravallion, 1993). In low-income countries, where administrative data on households' incomes ('means') are typically unavailable, targeting of welfare programs tends to rely on statistical procedures processing suitable proxies of households' means in a Proxy-Means Test (PMT). Alternatively, targeting may be decentralized through Community-based Targeting (CBT), where the choice of beneficiaries is delegated to local communities (Ravallion, 2003).

Both statistical and decentralized targeting methods have their pros and cons, so that from a policymaker's perspective each approach may be chosen on reasonable grounds. Existing studies mention superior cost-effectiveness (Chambers, 1994b) and higher satisfaction rates (Alatas et al., 2012; Schüring, 2014; Robertson et al., 2014) as two advantages of community-based over statistical targeting methods. In addition, local participative assessments are found to consider more poverty dimensions than only consumption (Alatas et al., 2012; Van Campenhout, 2007) and to improve local ownership and sustainability of the underlying program (Robertson et al., 2014). On the other hand, decentralization of political decision making is more susceptible to capture by local elites (Conning and Kevane, 2002; Bardhan and Mookherjee, 2006). In contrast, PMT-based targeting is the more transparent and replicable procedure, and can avoid potential principal-agent problems (Ravallion, 1993). Hence, if a central government aims to retain control over the targeting procedure, preference will likely be given to statistical methods. In a comprehensive review of targeted anti-poverty interventions around the global South, Coady et al. (2004a) find that statistical and decentralized targeting methods are similarly often employed. They conclude, however, that '(t)here is little documented evidence on community-based targeting as compared to other methods' (see also Conning and Kevane, 2002).

In this paper we aim to fill this research gap by investigating which method, community-based or statistical targeting, targets consumption-poor households more accurately. We compare community-based targeting with five frequently used PMT procedures, where our reference is a hypothetical targeting outcome based on survey consumption. In addition, we study how the targeting accuracy of the two families of methods compares across alternative PMT specifications, across rural and urban sectors, and across community characteristics. Finally, we evaluate the cost-effectiveness of each procedure. In our empirical analysis, we combine data from community targeting exercises conducted in 35 villages and 22 urban neighborhoods in north-western Burkina Faso in 2009 with household survey data that includes consumption as well as common proxy-means variables. We also use census data to construct community characteristics, and administrative cost data for a cost-effectiveness analysis.

All PMT indices which we consider have in common that they are calculated as weighted averages of potentially transformed proxy-means variables, while they differ along three dimensions, the set of indicators, the way these indicators are transformed into proxy-variables, and the weights used to aggregate the proxy-variables into a single index. Accordingly, we distinguish between four types of proxy-means tests; first, a PMT based on a linear regression model, which typically employs a large number of indicators available in census data. The indicators are usually not transformed and the weights are obtained from a regression of consumption on proxy-means variables (Filmer and Scott, 2012; Klasen and Lange, 2014). We will call this procedure *Consumption-oriented PMT*. Alternatively, the weights can be obtained from the joint distribution of the indicators themselves through Principal Component Analysis, or PCA for short (Filmer and Pritchett, 2001). We will call this procedure *PCA-based PMT*. Third, we consider two scorecards which rely on a limited set of transformed indicators, India's *Below the Poverty Line* scorecard (Government of India, 2002) and the *Poverty Scorecard Index*, a targeting tool popular among practitioners (Schreiner, 2015). Finally, we calculate a *Multidimensional Poverty Index*. Following Alkire and Santos (2010), in this approach all indicators are first transformed into binary deprivation indicators and the index equals a weighted deprivation count.

Our findings are as follows. First, community-based targeting is substantially less accurate than the consumption-oriented proxy-means test but more accurate than several other common PMTs. It is about as accurate as the best-performing PMTs not relying on consumption information for the construction of weights, the PCA-based PMT and the Below the Poverty Line scorecard. Second, relative to PMT methods, CBT performs slightly better in urban than in rural areas. Third, targeting errors of all PMTs and CBT respond almost identically to community characteristics, namely community size, economic inequality and heterogeneity along ethnic and religious lines. Finally, we find the consumption-oriented and PCA-based PMTs to be more cost-effective than community-based targeting only for very large transfer amounts. Hence, for common anti-poverty programs, decentralized targeting is by far the more cost-effective method in our context when the reduction of consumption poverty is the targeting objective.

Within the vast economic literature on targeting of welfare programs, our study contributes to the topic of targeting accuracy.[1] Until recently, the literature on this topic has followed a rather narrow approach: the focus is typically on one specific targeted anti-poverty program at a time and targeting accuracy is measured by the share of households meeting the program's targeting criteria in all beneficiary households (Ravallion, 2009). The empirical analysis usually combines households' self-reported program eligibility with socio-economic variables to estimate the program's targeting accuracy.[2]

A more recent set of studies has taken a broader approach to the topic of targeting accuracy by comparing alternative targeting methods in one empirical setting. This small but rapidly growing literature employs consumption as the reference and the variation in targeting methods comes either from alternative treatments (Alatas et al., 2012) or hypothetical calculations with household-level survey data (Filmer and Scott, 2012; Karlan and Thuysbaert, 2013; Klasen and Lange, 2014). Within this recent comparative targeting accuracy literature one can distinguish two branches. The first one contains comparisons of various alternative proxy-means tests' targeting accuracy (Grosh and Baker, 1995; Filmer and Scott, 2012; Klasen and Lange, 2014), while the second branch consists of comparative assessments of community-based targeting and one specific PMT (Alatas et al., 2012; Karlan and Thuysbaert, 2013).

Our main contribution is to merge these two so far disconnected branches of the recent comparative literature on targeting accuracy. We achieve this by comparing the accuracy of CBT with the five most prominent PMTs in one empirical setting. In particular, we are first to compare CBT with all major PMT methods, including a comprehensive PCA-based PMT, in a comparative targeting accuracy analysis. Further innovations are that we differentiate between rural and urban sectors, consider the role of community characteristics, and carry out a careful cost-effectiveness analysis with administrative cost data. An additional contribution is that ours is the first com-

[1] Other prominent themes are leakage (Alatas et al., 2013b; Niehaus and Atanassova, 2013), elite capture (Alatas et al., 2012, 2013a; Panda, 2015), agency problems in decentralization (Galasso and Ravallion, 2005; Banerjee et al., 2014), and communities' poverty perceptions (Van Campenhout, 2007; Kebede, 2009; Alatas et al., 2012).

[2] Some prominent examples are Banerjee et al. (2007) for food distribution, housing and employment schemes in India, Skoufias et al. (2001) for Progresa in Mexico, Ahmed and Bouis (2002) for food subsidies in Egypt, Handa et al. (2012) for cash transfer programs in Malawi and Kenya, and Castañeda (2003) for Columbia's SISBEN. We describe this latter program in more detail in section 2. The review by Coady et al. (2004a) summarizes studies of 122 anti-poverty programs in 48 countries.

parative study of targeting accuracy for a sub-Saharan African context, where community-based methods have been employed more frequently than anywhere else (Garcia et al., 2012; Handa et al., 2012).

The remainder of this paper is structured as follows. In the next section we briefly review proxy-means tests and community-based targeting. The empirical setting is the subject of section 3. Section 4 introduces the empirical methodology. Section 5 contains the empirical results. In section 6 we discuss our findings. The final section concludes.

2 Statistical versus community-based poverty targeting

PMTs are a relatively recent but increasingly popular targeting tool in low-income countries (Coady et al., 2004a). In Latin America, PMT-based targeting has been used for large-scale cash-transfer programs in Mexico (Progresa/Oportunidades), Colombia (Familias en Acción), and Chile (PASIS and SUF). National food-subsidization programs such as those in Indonesia and Egypt use PMT-based targeting as well (Coady et al., 2004a; Ahmed and Bouis, 2002). PMTs are also popular among small-scale poverty reduction programs, where often only a small set of indicators is used. In practice, PMT-based targeting is often combined with a first-stage geographic targeting procedure (Coady et al., 2004a).[3]

Proxy-means testing typically relies on self-reported (and sometimes validated) information on a household's demographic, occupational, and asset structure to calculate for each household in a population a wealth index, the approximate 'means' of a household.[4] A household is targeted if its index value falls short of a pre-specified cutoff, which may be defined in absolute terms or as a population quantile. The wealth index is calculated as a weighted average of proxy-means variables and, in general, involves three choices; first, the set of indicators: given the high cost of data collection for entire populations, often indicators available from existing census data are used (Ravallion, 2009); second, the transformation of each indicator into a proxy-means variable, and third the index weights. We discuss the five PMTs which we consider along these lines and contrast them with community-based targeting.

[3] Two examples are the Mexican Progresa program (Skoufias et al., 2001) and the national cash transfer program in Indonesia (Alatas et al., 2012).

[4] Such information is usually preferred over self-reported income or expenditures for several reasons. First, collecting detailed income or consumption data for an entire population is very costly. Second, both measures leave more room for strategic misreporting and can be hardly verified by the enumerator. Finally, income often suffers from considerable short-term fluctuations (Alatas et al., 2012).

Consumption-oriented proxy means testing

This method typically uses a large set of proxy-means variables. The indicators are often obtained from census data and may or may not be transformed (Filmer and Pritchett, 2001; Klasen and Lange, 2014; Alatas et al., 2012). Weights are obtained from a regression of per capita consumption on the set of proxy-means variables. More precisely, regression coefficients are used as weights for the entire population. Hence, for a given household, its wealth index equals its predicted value of consumption in a linear regression sense. The data used for this exercise typically comes from a sample survey (Filmer and Scott, 2012; Klasen and Lange, 2014). This approach, hence, requires consumption data for at least a subset of households. When a program's purpose is to reduce consumption poverty, this approach is easily motivated by the fact that the resulting index is the best linear predictor of household consumption given the information available in a population census. Most of the recent comparative targeting accuracy literature analyzes this PMT, and the large-scale cash transfer programs in Mexico (Progresa) and Indonesia (BLT) are two prominent applications.

Principal component analysis

In what we call a PCA-based PMT weights are obtained from the joint distribution of the proxy-means variables themselves. Specifically, principal component analysis (PCA) is used to reduce a large set of proxy-means indicators to a small set of orthogonal linear combinations of the variables that best capture the variation in the original indicators. Following Filmer and Pritchett (2001), the first principal component is used as wealth index and its so-called factor loadings as weights.

The PCA-based index is most frequently used to proxy a household's socio-economic status in the absence of consumption data and has been particularly popular in health-related studies that rely on data from Demographic and Health Surveys (DHS). Depending on the discipline, the PCA-based index is named differently; in health and epidemiology it is usually called 'wealth index' (Howe et al., 2009) or 'index of socio-economic position' (Wagstaff and Watanabe, 2003), while in economics and demography it is often referred to as 'asset index' (Sahn and Stifel, 2003). No study in the recent targeting accuracy literature considers a comprehensive PCA-based PMT.[5] While in general less popular in the area of targeting, we are aware of one prominent application,

[5]Karlan and Thuysbaert (2013) consider a PCA-based index where five housing variables are aggregated into a housing index.

Columbia's *Sistema de Selección de Beneficiarios para Programas Sociales* (SISBEN), which has been in effect for more than twenty years. In this system, eligibility for various social programs relies on a wealth index with 13 proxy-means variables and PCA-based weights (Castañeda, 2003).

Scorecards

In comparison to the just discussed two PMTs, scorecards typically rely on a smaller set of indicators. By means of a scorecard each indicator realization is transformed into an indicator score, which typically takes only integer values. The sum of indicator scores gives the wealth index, here called wealth score. The mappings of indicator realizations into indicator scores simultaneously delivers the transformation of each indicator and the weighting between indicators. A property the scorecard approach has in common with all other PMTs considered here is that the final wealth index is additively separable in the individual indicators. The indicator scores are usually obtained using either regression techniques or common sense. We include the following two scorecard-based PMTs into our targeting accuracy analysis.

First, we consider the Poverty Scorecard Index (PSI). It was initially developed by a microlender in Bosnia-Herzegovina and primarily used to measure the microfinance institution's outreach to the poor and the institution's impact on customers' welfare. It has subsequently been managed on a global scale by Grameen Foundation and, lately, the non-governmental organization Innovations for Poverty Action (IPA), where it is called Progress out of Poverty Index (PPI). The index has also been used for targeting of anti-poverty interventions and is increasingly used in contexts other than microfinance, such as health and education (Schreiner, 2015; Alkire et al., 2015). According to IPA's 2014 report, the PSI is being used by more than 200 organizations for anti-poverty programs around the global South. Among them are the Bangladesh Rural Advancement Committee (BRAC), the Grameen Bank, the Ford Foundation, and the International Finance Corporation (Innovations for Poverty Action, 2014). Customized scorecards for 46 countries are available as of 2016. The selection of indicators is based on 'statistics and judgment' and, similar to the consumption-oriented PMT, indicator scores are obtained from national expenditure surveys through regression techniques with consumption poverty as the dependent variable (Schreiner, 2015, p.556). In our analysis, we use the 2011 version of the PPI scorecard for Burkina Faso developed by Mark Schreiner, which we have retrieved from IPA's website in January 2016.

Second, we calculate an index based on the Below the Poverty Line (BPL) scorecard, which was developed by an expert group commissioned by the Indian government in 2001 (Government of India, 2002). The expert group's task was to develop an index that allows to assess each household's quality of life (Government of India, 2002, paragraph 3.24.3). The BPL criterion is used in India's public food distribution system and for several poverty alleviation programs administered by the Ministry of Rural Development (Sundaram, 2003). The indicator selection builds on India's 2001 census questionnaire. The scorecard includes thirteen indicators and a score of between zero and four is assigned to each realization. Its methodology has been vividly debated in the policy as well as the academic community (Sundaram, 2003; Banerjee et al., 2007; Alkire and Seth, 2013).

The Multidimensional Poverty Index

In this approach all indicators are first transformed into binary deprivation indicators and the relevant poverty index is a weighted deprivation count. The so-called Global MPI (Alkire et al., 2015) comprises ten indicators from three different dimensions of well-being, education, health, and standard of living. Its weights are equal across and within the three dimensions of well-being, such that the sum of all indicator weights within a dimension always equals one third. The MPI and scorecards have in common that they involve normative judgments regarding the selection and the transformation of indicators, as well as the choice of weights.

The Global MPI was developed for the United Nations Development Programme. It is annually reported in the Human Development Report and is calculated for more than one hundred countries (Alkire and Santos, 2014). Its primary purpose is the measurement of multidimensional poverty in the developing world given common data constraints. In addition, Alkire and Santos (2010) argue that the methodology underlying the global MPI may also serve as a tool for the targeting of anti-poverty programs (see also Alkire et al., 2015). Along these lines, four recent studies compare targeting based on the MPI methodology with other targeting approaches, such as the BPL scorecard (Thomas et al., 2009; Alkire and Seth, 2013; Azevedo and Robles, 2013; Robano and Smith, 2013). We are aware that the MPI intends to capture a different, more multidimensional concept of poverty than our consumption benchmark. Due to its popularity in policy applications and its ambitions for targeting, we find it nonetheless of interest to include it in our comparative analysis to see how suited (or not) it is for proxying for consumption poverty.

Community-based targeting

In community-based targeting the choice of beneficiary households is delegated to local communities (Ravallion, 1993). The approach usually includes a so-called community wealth ranking and has earlier often been called *Rapid Rural Appraisal*, or RRA for short. According to Chambers (1994a), RRAs were pioneered in the late 1970's because of a growing discontent with statistical poverty assessments and, in particular, their relatively high costs. Since then, community wealth rankings have not only been used for poverty assessments (see, for instance, Devereux and Sharp, 2006; McGee, 2004; Van Campenhout, 2007) but have also emerged as a targeting tool.

Recent examples include small to medium-scale asset creation programs geared at the ultra-poor and funded by the Consultative Group to Assist the Poor (CGAP). Karlan and Thuysbaert (2013) analyze one such program in Honduras and Peru. Banerjee et al. (2007) investigate CBTs within the context of a similar asset-creation program in rural India. Community-based targeting is also sometimes used on a larger scale. In their cross-country analysis of targeted anti-poverty interventions, Coady et al. (2004a) find that, overall, community-based targeting is similarly often used as proxy-means testing, equally popular on all continents and especially wide-spread in very poor countries.

[Table 1 about here]

To the best of our knowledge, there is no structured summary of the procedural details of community-based targeting in the extant literature. Therefore, in Table 1, we review fifteen studies of CBTs, inclusive of the intervention studied in this paper (Souares et al., 2010), which are sufficiently explicit regarding procedural details. Eight have been implemented in sub-Saharan Africa. All fifteen instances have in common that the targeting exercise involves the entire community, at least at an initial stage. They differ along four characteristics, which are set out in columns 1 to 4 of Table 1. First, most CBT exercises start with a public focus group discussion to elicit communal wealth and poverty perceptions, and sometimes also to define wealth brackets. Second, in most of the CBTs summarized in Table 1, all households of the community are assigned to the different wealth brackets. Third, in eight of the studies, a complete wealth ranking of households is undertaken by sorting households within each wealth bracket subsequently. Finally, there is variation regarding agency. In particular, the assignment of households to wealth brackets as well as the comprehensive ranking may be carried out either by the community as a whole or by a small number of elected local informants.

3 Empirical setting and data

3.1 The community-based targeting exercise

The empirical setting of our study is the administrative department of Nouna in the North West of Burkina Faso, depicted in Figure 1. At the time of our study, it was inhabited by a population of about 80,000 individuals of whom two-thirds live in villages and one third in and around the town of Nouna, the only urban area (see Figure A1 of the Online Appendix for a detailed map). The majority of inhabitants are farmers. Since 2006 all households in the study area have had the opportunity to purchase micro health insurance from a formal not-for-profit provider. Despite of a seemingly affordable insurance premium, overall health insurance enrollment rates had remained far below expected levels. As enrollment rates were especially low among poor households (Souares et al., 2010), in 2007 the insurer decided to offer a fifty per cent discount on the premium to the poorest quintile of households in each community. To be precise, the insurer's program proposal to the ethical review committee of Burkina Faso states the intention to "identify the twenty per cent poorest households (...) such that they could benefit from health insurance at lower prices" (Savadogo and Souares, 2007, p.2).

[Figure 1 about here]

For the targeting of households the insurer employed CBT exercises, which were carried out at the level of villages and urban neighborhoods during the first quarter of 2009.[6] In each community, the procedure started with a publicly convened community meeting, where the facilitators first informed about the purpose of the meeting. Detailed transcripts of these meetings confirm that the official targeting objective of the insurer stated above was also communicated on the ground (Savadogo et al., 2015). The facilitators then initiated a focus group discussion to elicit criteria regarding poverty and wealth. The two most often stated criteria for characterizing poverty, 'has insufficient food' and 'has nothing', directly or indirectly relate to consumption (Savadogo et al., 2015, p.8).

[6]For the purpose of the targeting exercise, each of the seven administrative sectors of Nouna town was divided into up to four neighborhoods with similar numbers of households (see Figure A2 for a map).

The community was then instructed to use these criteria for defining three to four wealth brackets. In a third step, the community assembly elected three local key informants by acclamation. Physically separated from the assembly and each other, each key informant first assigned each household to one of the previously defined wealth brackets and, second, ordered all households within each bracket. While the number of households eligible in the respective community, m say, was fixed in advance by the implementer, neither the community nor the key informants were briefed about it. In a final step, the set of beneficiary households was determined according to the following rule: First, households which had been ranked among the m poorest by all three informants were automatically eligible (about 40 percent of beneficiary households; see Table 2). Second, all households which had been ranked among the m poorest by exactly two informants were included, provided that the resulting number of beneficiaries did not exceed m, and, in a consultation among the key informants, the remaining beneficiary households were chosen from the set of households which had been ranked among the m poorest by exactly one of the three informants previously. Otherwise, only a subset of the households which had been ranked among the m poorest by exactly two informants were included. In particular, households in this group were sorted by their median rank and those with the highest median ranks were excluded. This occurred in ten of the 57 communities. On average, the entire exercise took half a day.

3.2 Data

For the empirical analysis we match a cross-sectional household survey with data from the community-based targeting exercises. The household survey covers 748 households in all of the 35 villages and 22 urban neighborhoods. It involves a clustered stratified random sampling methodology. Data collection took place between September and November 2009, right after the rainy season. Our CBT data set contains all three key-informants' ranks as well as the final eligibility status for 18,871 households.

Table 2 reports summary statistics of the targeting exercise by sector. The average community size is about 110 households and 20 per cent of households in each community were targeted. On average, there is a sizable positive correlation of 0.66 between the three informants' rankings as measured by the Spearman rank correlation coefficient, and this applies to rural and urban communities alike. Nonetheless, if we define an individual key informant's target group by his m lowest-ranked households, a unanimous agreement occurs for only 40 percent of beneficiary households.

[Table 2 about here]

The merged dataset contains 561 households, for which summary statistics are set out in Table 3. Households are relatively large and literacy rates low. Agriculture is the predominant activity in villages and even for half of the urban households. Livestock possession is wide-spread, especially in the rural sector. Targeted households appear to be slightly oversampled with a targeting share of around 0.25 in comparison to 0.20 in the population.

As reference variable for our subsequent targeting accuracy analysis, we use the value of non-durable items purchased by the household head during the thirty days preceding the interview, as recorded in the household sample survey. We shall point out here that our consumption variable does not include the value of self-produced consumption items or purchases of durable (low-frequency) consumption items. Our household survey makes no attempt to record the value of the household's entire consumption. From our experience in the field, however, we think that household head expenditures are a good proxy of mean per capita consumption. Moreover, we also conduct a robustness check with an alternative consumption measure exploiting the fact that our survey includes high-frequency consumption expenditures of each adult member of a household. When we use the sum of these expenditures and divide by the number of household members as a proxy for per-capita consumption, all of our results remain qualitatively unchanged. Because of our impression that household heads' responses are more reliable on average, we only present the results with household-head consumption in the main text. The respective additional results are available in the appendix (Table A7).

[Table 3 about here]

4 Empirical methodology

4.1 Target sets

In our main analysis we construct and compare seven different sets of target households. First, the set of households actually targeted by the communities. We denote the corresponding set of target households in community c in our sample by T_c^{CBT}. For our sample, the remaining six hypothetical target groups are constructed from the household survey data as follows. Let n_c^{CBT} denote the number of sample households targeted by the community-based method in community c.[7] To construct T_c^m, the hypothetical target set based on method m in community c, we first sort all sample households in c by the wealth index of method m and select the n_c^{CBT} households with the lowest index values. The aggregate sample target set is the union set $T^m = \cup_{c=1}^{C} T_c^m$, where C denotes the number of communities. Following the recent comparative targeting accuracy literature (Alatas et al., 2012; Filmer and Scott, 2012; Karlan and Thuysbaert, 2013; Klasen and Lange, 2014), we take consumption as the benchmark wealth index and denote by T^{CON} the benchmark target set. We assess the targeting accuracy of method m in terms of the overlap of T^m with T^{CON}. In the following, we make precise how we calculate the five PMT indicators in detail. For considerations of space, estimation outputs and calculations are relegated to the Online Appendix (see Table A1 for details). Table 4 provides an overview of the five PMT methods regarding indicators and weights.

[Table 4 about here]

Consumption-oriented PMT

For the consumption-oriented PMT we define a dummy variable $Elig_{ci}^{CON}$ equal to one if household i in community c is targeted according to our benchmark. We then estimate the linear regression model

$$Elig_{ci}^{CON} = \alpha_c + \beta x_{ci} + u_{ci},$$

where x_{ci} is a vector of proxy variables, β is the corresponding coefficient vector, α_c are community fixed effects, and u is a stochastic error term. We conduct this regression analysis separately for rural and urban households (see Table A2 in the Online Appendix for the regression output). In a second step, index values are calculated for each household as $\widehat{Elig}_{ci}^{CON} = \widehat{\beta} x_{ci}$. Third, for each community, households are sorted with respect to the index value and the n_c^{CBT} lowest ranked households are assigned to $T_c^{\widehat{CON}}$.

PMT based on Principal Component Analysis

We apply principal component analysis (PCA) to obtain weights that derive from the joint distribution of the proxy-means variables themselves. Our PCA-based PMT employs the same set

[7] To illustrate, consider a village with 100 households from which 20 have been targeted by the community-based method. Suppose that, from this village, the household survey includes 10 households with 3 sample households targeted and 7 not targeted. While the population targeting set contains 20 per cent of all households, all of our seven sample targeting sets will always contain precisely 3 sample households from that village.

of indicators as the consumption-oriented PMT. To focus on within-community differences across households, we first subtract community means from each indicator. Following Filmer and Pritchett (2001), we take the first principal component as wealth index and the corresponding factor loadings as weights (see Appendix Table A3 for details).

Poverty Scorecards

We first discuss the Poverty Scorecard Index (PSI). We use the 2011 Burkina Faso poverty scorecard from IPA's website[8] to calculate indicator scores and to construct the hypothetical target set T^{PSI}. Of its ten indicators we omit one which is not covered in our household survey, 'Does the household own a bed or mattress?'. However, as this indicator accounts for not more than three per cent of the full score, we are confident that this omission should not threaten its overall performance. Table A4 of the Online Appendix provides details about this scorecard.

Second, we employ India's Below the Poverty Line scorecard (Government of India, 2002) to construct the respective hypothetical target set T^{BPL}. For reasons of data availability we have to omit one of the thirteen original indicators, 'food security'. In addition, we substitute the original indicators 'availability of normal wear clothing', 'type of indebtedness', 'reason for migration from household', and 'preference for assistance' with 'drinking water source', 'type of risk coping', 'emigration incidence', and 'use of transfers received', respectively (see Online Appendix Table A5 for details).

The Multidimensional Poverty Index

We build on the Global Multidimensional Poverty Index (MPI) by Alkire and Santos (2010). For reasons of data availability, we make two modifications regarding the health dimension. We omit the nutrition indicator and substitute the mortality indicator by the incidence of a recent severe health shock, which is recorded in our sample survey with a recall of one month. We adjust the weights for this dimension accordingly (see Online Appendix Table A6 for details).

4.2 Targeting accuracy

We take the benchmark target set T^{CON} and assess the targeting accuracy of CBT and the five PMTs in terms of the mean targeting error. The latter is defined as the proportion of households

[8] See http://www.progressoutofpoverty.org/country/burkina-faso.

which are erroneously classified as either poor or non-poor. To be precise, when there are I_c sample households in community c and n is the total number of observations in the data set, $n = \sum_{c=1}^{C} I_c$, the targeting error for method m is calculated as

$$Err_m = \frac{1}{n} \sum_{c=1}^{C} \sum_{i=1}^{I_c} \begin{bmatrix} \mathbb{1}\{ \text{ household } ci \text{ is in } T^{CON} \text{ and not in } T^m \} + \\ \mathbb{1}\{ \text{ household } ci \text{ is in } T^m \text{ and not in } T^{CON} \ \} \end{bmatrix}, \qquad (1)$$
$$m = \{\widehat{CON}, PCA, PSI, BPL, MPI, CBT\},$$

where $\mathbb{1}\{\}$ denotes the indicator function. Notice that the mean targeting error is the sum of two types of errors. An exclusion error (false negative) occurs when consumption-poor households are not targeted by the targeting method under consideration. Conversely, households not targeted by consumption but by the targeting method under consideration contribute to an inclusion error (false positive). The Venn-diagram in Figure 2 illustrates this graphically.

[Figure 2 about here]

As a benchmark for comparison, we also calculate the targeting error when households are targeted at random. For the sample targeting probabilities of 26 and 24 per cent for rural and urban communities, respectively, the probabilities for erroneous targeting under random targeting are $0.74 \cdot 0.26 + 0.26 \cdot 0.74 = 0.38$ and $0.76 \cdot 0.24 + 0.24 \cdot 0.76 = 0.36$, respectively. When we compare two alternative targeting procedures, A and B, the object of interest is the difference in the mean targeting error. To conduct statistical inference, we estimate the regression equation

$$Err_{cim} = \gamma + \delta \cdot \mathbb{1}\{m = B\} + u_{cim},$$

where Err_{cim} is the targeting error of observation ci with procedure m, the term in brackets in equation 1, and u is a stochastic error term. Procedure A defines the reference category and the least squares estimate $\widehat{\delta}$ equals the difference between the mean targeting errors of procedures B and A. The data set for this exercise has $2n$ observations as every household appears twice, once with procedure A and once with procedure B. We cluster standard errors at the household level because only the differences $Err_{ciB} - Err_{ciA}$ can safely be assumed to be independent.

5 Results

5.1 Targeting accuracy

Table 5 reports mean targeting errors (MTEs) as well as exclusion and inclusion errors by sector. For the rural sector MTEs are set out in the first column. MTE values range from 0.15 to 0.35, which amounts to a reduction of the random MTE of 61 to 8 per cent. The consumption-oriented PMT has by far the lowest MTE with less than every sixth household wrongly classified. The difference to the next-best method, the PCA-based PMT, is eight percentage points, which is statistically different from zero at the five percent significance level. Consumption-oriented targeting reduces the MTE in a statistically significant fashion relative to any of the other techniques (see Appendix Table A8). On the other end, across sectors, the Poverty Scorecard Index and the MPI deliver only marginal and statistically insignificant (at the five percent level) improvements relative to random targeting, while the Principal Component performs well in villages and urban neighborhoods alike. Averaged across sectors, it is the best performing PMT not involving consumption data for obtaining weights, closely followed by the BPL scorecard, whose performance is not statistically different at conventional levels. Regarding community-based targeting, there are two salient findings emerging from Table 5. First, averaged across the two sectors (that is across columns 1 and 4), CBT is about as accurate as the two best performing PMTs not requiring consumption data, PCA and the BPL scorecard. With mean targeting errors roughly twice as large as those of the consumption-oriented PMT, the average performance of these three procedures is not statistically different at conventional levels. Second, in relation to the competing PMT methods, CBT performs somewhat better in the urban neighborhoods than in the villages. In the urban areas, CBT has a slightly smaller mean targeting error than the PCA-based PMT and the BPL scorecard. The two differences fail to be significantly different from zero, however, at conventional levels.

[Table 5 about here]

Table 5 also contains exclusion and inclusion errors, and the corresponding random targeting errors as reference. By construction, the number of erroneously included households always equals the number of erroneously excluded households. Accordingly, the values in columns 2 and 5 equal the mean targeting error divided by two times the sample targeting share of 0.26 and 0.24, respectively. The mean inclusion errors are a multiple of the respective exclusion errors, where the factor of proportionality is the sample targeting share, s say, divided by one minus s. We will return to the exclusion errors in our cost-effectiveness analysis.

In Table 6 we decompose targeting errors along the consumption distribution. In particular, we calculate exclusion errors separately for extremely poor and moderately poor households, and inclusion errors for households around the distribution's median as well as for relatively affluent households. We define the expenditure classes such that the shares of extremely and moderately poor households are roughly equal and sum up to the sample targeting shares of the community-based targeting exercises, 26 and 24 percent for rural and urban communities, respectively (see Table 3). The other two expenditure brackets contain the complementary sets of households and are defined such that they are roughly of equal size; for example in the rural subsample the affluent and around median expenditure brackets roughly contain the first and second 37 percent wealthiest households as measured by consumption, respectively. As a consequence, the mean exclusion and inclusion errors in Table 5 are the arithmetic means of the respective consumption-bracket-wise errors in Table 6.[9] While the point estimates suggest that, relative to the BPL scorecard, community-based targeting is more accurate in identifying extremely (moderately) poor households in rural (urban) areas, none of the differences between the PCA-based PMT, the BPL scorecard and the CBT are statistically significant at conventional levels. When averaged across sectors, the four best-performing procedures all have in common that the extremely consumption-poor are identified more accurately than the moderately poor, as would be expected. This pattern is statistically significant for the consumption-oriented and PCA-based PMTs and CBT at the five percent significance level. In this regard, community-based targeting is no different from the three best-performing statistical procedures.

[Table 6 about here]

5.2 Weights and indicators in proxy-means testing

As mentioned earlier (see Table 4), PMTs vary along three dimensions, the set of indicators, the transformation of indicators into what may be called proxy-means variables or indicator scores, and

[9] The numbers of households in columns 1 and 2, 3 and 4, 5 and 6, and 7 and 8, respectively, are not exactly equal because of communities where the CBT sample target set or its complement contains an odd number of households. In that case, we have chosen to allocate the median household of the consumption sample target set to the moderately poor group and the median household of the complementary group to the around-median group. Changing this rule does not affect the results substantively.

the weighting. In section 5.1 we have found that the five different PMTs we consider result in very different targeting errors. In this section, we explore to what extent these differences in targeting accuracy can be attributed to the sets of indicators on the one hand and the weighting schemes on the other. Accordingly, Table 7 reports MTEs for various hypothetical PMT specifications by sector (see Appendix Tables A8 and A9 for statistical differences). The shaded cells contain MTEs of the five PMTs considered in the previous analyses. Ten more PMTs are constructed by varying the five existing PMTs along two dimensions, the set of indicators (in columns), and the weighting method (in rows).

[Table 7 about here]

For the role of variable selection it is interesting to compare the first three columns, where the total number of variables is similar. In our context, the variables employed by the MPI work relatively poorly for targeting consumption-poor households. Across sectors and weighting methods the MPI has the highest targeting error. Turning to weights, the Poverty Scorecard Index has the potential to outperform the MPI as well as the BPL-based scorecard when its weights are appropriately modified. The broad picture emerging for the three PMTs involving normative choices of indicators, transformations and weights looks such that the PSI is strong regarding the set of variables but poor regarding the choice of implicit weights. The MPI performs poorly regarding both, while for the BPL-based scorecard both the set of indicators and the choice of weights are fair.

Finally, for the weights of the consumption-oriented PMT, we find that the choice of the dependent variable in the regression delivering the weights makes a non-negligible difference. When the logarithm of consumption is used (as in Alatas et al., 2012, and others) rather than the dummy variable *Eligible by consumption*, the MTE increases from 10 to 16 percent ($\alpha = 0.10$) for the urban sector. This suggests that there are important non-linearities in the true regression function that are better dealt with by our dichotomous specification of the consumption variable.

5.3 Community characteristics and targeting accuracy

Drawing on census data and a vital registration system, we construct four community-level characteristics, community size, economic inequality, as well as indices of ethnic and religious heterogeneity. Our measure of economic inequality is a Gini coefficient calculated for a PCA-based asset index involving 25 commonly used census variables. For our measures of heterogeneity, we calculate two indices commonly known as ethno-linguistic fractionalization, which equals the probability that two randomly drawn individuals from the same community belong to different ethnic or religious groups, respectively. Table 2 contains summary statistics of these variables and Table 8 the estimation results. Since there would only be 35 and 22 observations for rural and urban communities, respectively, we pool the two sectors for this exercise. For ease of interpretation, all four explanatory variables of interest have been standardized.

[Table 8 about here]

We find that the targeting errors of all six methods increase with the size of the community. Increasing community size by one standard deviation increases the mean targeting error by about 3 to 6 percentage points, depending on the targeting method. This relationship is less pronounced for the consumption-oriented PMT. While such a pattern is certainly expected for community-based targeting, we find it to some extent surprising that greater community sizes do not put CBT at a disadvantage relative to the statistical procedures. We do not find a statistically significant relationship between economic inequality and targeting accuracy. Under plausible assumptions one would expect the opposite, that greater economic heterogeneity would make targeting outcomes across methods more accurate. Regarding ethnic and religious heterogeneity, there is no clear pattern. While targeting is more accurate in ethnically more heterogeneous communities, the opposite is true for religion. Nonetheless, as for the other two community characteristics, all methods respond very similarly to changes in community heterogeneity, in particular the consumption-oriented PMT and community-based targeting. To summarize, according to the evidence we find, none of our community characteristics puts one specific method, in particular statistical or community-based targeting, at an obvious advantage.

5.4 Cost-effectiveness analysis

Given the superior targeting accuracy of the consumption-oriented and partly also the PCA-based PMT over CBT we will finally compare the cost-effectiveness of the three methods. Mayoux and Chambers (2005, p.283) state that 'a key advantage of participatory methods is their cost-effectiveness in rapidly bringing together information and knowledge from many participants.' In the same vein, the meta-studies of Coady et al. (2004b, p.61) and Conning and Kevane (2002) attribute the lower administration costs of CBT to the wage differential between external enumerators and community agents. When a social program's intention is to reduce poverty and CBT is cheaper but at the same time less accurate than statistical targeting, there is a trade-off and the relatively inexpensive CBT will be more cost-effective than statistical targeting for social programs with relatively small transfer amounts, while the opposite holds for large transfer amounts. This is precisely what Alatas et al. (2012) find in their Indonesian context (Table 5, columns 1 and 2, of their Online Appendix). In the present analysis we will calculate transfer-amount thresholds for the competing targeting methods. In this context, we make two innovations. First, on the cost side, we consider alternative scenarios regarding the availability of data for statistical targeting. Second, on the benefit side, we derive explicit formulae linking exclusion errors from the estimations to poverty reduction instead of relying on simulations (as in Ravallion, 2009; Alatas et al., 2012; Klasen and Lange, 2015).

We use cost information from the 2009 community-based targeting intervention and approximate implementation costs for the statistical methods based on data collection campaigns in 2010 (Lietz et al., 2015). All figures are inflated to 2014 CFA (African Financial Community) francs using the consumer price index of Burkina Faso and converted to 2014 US dollars using the 2014 average exchange rate of 526 Francs per dollar. Total implementation costs for CBT amount to \$2,373. For the PMTs we consider three cost scenarios. First, we assume that census and household survey information are freely available and only data processing costs of \$5,761 for the consumption-oriented and \$2,665 for the PCA-based PMT accrue. The difference between the two amounts reflects the extra work required to process the consumption survey data for the consumption-oriented PMT. In addition, our second scenario takes into account the data collection costs for the household consumption survey of \$41,899, which is needed to calibrate the consumption-oriented PMT. Hence we calculate a total cost of \$47,660 for the consumption-oriented PMT, while the cost of the PCA-based PMT remains unchanged. In the third scenario, for both PMTs, we add the cost of collecting the census data of \$36,053, amounting to total costs of \$83,713 and \$38,718 for the consumption-oriented and PCA-based PMT, respectively.

In line with existing literature (Ravallion, 2009; Alatas et al., 2012), we consider the extent of poverty reduction, measured in terms of consumption, as the social benefit of an anti-poverty program. We calculate a poverty measure of the FGT class (Foster et al., 1984) at the household level, where, for each community, we set the poverty line equal to the consumption threshold implied by the twenty percent population targeting share (see Table 2). Given the purpose of the community targeting exercise studied here, to identify the 20 percent poorest households in each community, this definition of poverty seems appropriate. Rather than conducting poverty-reduction simulations (as in Ravallion, 2009; Alatas et al., 2012; Klasen and Lange, 2015), we calculate the extent of poverty reduction with a first-order Taylor approximation that yields an explicit relationship between the exclusion error and poverty reduction.

To fix ideas, we write the benefit-to-cost ratio of an anti-poverty program which transfers t dollars to each eligible household and relies on targeting method m as

$$BCR(t)^m = \frac{|\Delta P^m|}{Cost^m},$$

where ΔP^m denotes the change in the poverty index (at the level of households) and $Cost^m$ the total cost of the program divided by the number of households. Benefits as well as costs are, of course, increasing functions of t. We take the total cost to be the sum of the aggregate transfer benefit and targeting costs. For a given targeting method, the latter are a fixed cost, while the former are a variable cost proportional to t. We abstract from other program fixed costs, such as administrative costs of effecting individual benefits. In the Appendix we show that for the poverty gap index, on which we focus here,

$$BCR^m(t) \approx \frac{1}{p}\left[1 - ExclusionError^m\right] \frac{1}{1 + (t/TC^m)^{-1}},$$

where p denotes the poverty threshold in dollars and TC^m the (fixed) targeting cost per eligible household, i.e. the total targeting costs divided by the number of beneficiary households. The term in brackets may be called the inclusion probability of targeting method m, the probability that a consumption-poor household is correctly targeted by method m. The fraction t/TC^m equals the ratio of transfer benefits to targeting costs. In words, the benefit-cost ratio is a constant, which is independent of the method, times the product of the inclusion probability and a simple increasing transformation of the transfer-to-targeting-cost ratio. Equivalently, the said product equals the ratio of average benefit per consumption-poor household to program costs per poor household. We limit our attention here to the poverty gap index because it is the only FGT measure which is linear in the exclusion error as set out in Table 5.[10]

We now compare the benefit-to-cost ratios for community-based targeting with the consumption-

[10] In contrast, with the methodology outlined in the Appendix, the change in the headcount ratio is linear in the exclusion error at the poverty line, whose sample counterpart would suffer from much greater imprecision than the exclusion errors set out in Table 6.

oriented and PCA-based proxy means tests. Within our framework, the consumption-oriented PMT is always most cost-effective for programs with a large transfer benefit per eligible household, t say, because, as t tends to infinity, the limit of BCR only depends on the targeting method's inclusion probability. For small transfer benefits, in contrast, the ratio of the inclusion probability to the targeting cost is what matters for cost-effectiveness. For all three cost scenarios regarding statistical targeting, CBT always accrues less than half the targeting cost of the two PMTs. On the other hand, CBT's inclusion probability consistently exceeds half that of the statistical procedures (see Table 5 columns 2 and 5), implying that it is the most cost-effective method for anti-poverty programs with very small transfer amounts. Accordingly, Table 9 contains transfer-amount thresholds for pairwise comparisons of these three targeting procedures. When only data processing costs accrue (column 1), community-based targeting is more cost effective for transfer amounts of up to 1.68 and 2.63 dollars in rural and urban communities, respectively. When all data collection costs are taken into account, these figures increase to 67.64 and 90.32 dollars, respectively. It is also interesting to compare the two statistical procedures with each other. Recall that employing principal components does not require the use of consumption data. Accordingly, in cost scenarios 2 and 3, the consumption-oriented PMT is more cost-effective for only relatively large transfer amounts, at least in rural areas.

To put these figures in perspective, the effective average benefit per eligible household in our intervention, a discount on the premium for a twelve-months health insurance police, amounts to roughly \$1.28, which is less than the smallest break-even amount of any of the two PMT-methods. We conclude that, among the targeting procedures considered here, CBT was indeed the most cost-effective method for targeting consumption-poor households - even though CBT's targeting cost of \$2.07 per eligible (or consumption-poor) household amounts to more than three times the average transfer benefit received by a consumption-poor household (\$0.64, one minus CBT's average exclusion error of 0.5 times \$1.28). Given this seeming disproportion, would an untargeted subsidy have been more cost-effective? We show in the Appendix that the benefit-to-cost ratio of a universal transfer program approximately equals $0.2/p$, implying a break-even of CBT relative to the untargeted intervention at a transfer of \$1.38 dollars per eligible household. While this figure suggests that a universal transfer might have been more cost-effective, this simple calculation is only valid when the transfer per household does not vary along the consumption distribution. In our context, however, households not eligible for the benefit on average enrolled at more than twice the rate of eligible households, which would double an untargeted subsidy's cost relative to the naïve scenario just considered and reduce the break-even threshold of CBT to \$0.52. We conclude that, taking into account the wealth gradient in insurance demand, CBT is also more cost-effective than an untargeted intervention in our empirical context.

6 Discussion

In this section, we summarize our findings and make explicit how they contribute to the existing literature. First, regarding the performance of various PMTs, we confirm the common and little surprising finding that the consumption-oriented PMT is by far the most accurate method. Our findings are partially in accordance with Filmer and Scott (2012), who find no statistical differences when comparing the PCA-based PMT with other common PMTs that do not involve consumption data for the calibration. In our setting, the PCA-based PMT performs similarly well as the BPL scorecard, and significantly better than the PSI and MPI. Second, regarding CBT and PMT in comparison, our targeting accuracy results are similar to the results obtained in a large field experiment in Indonesia, where Alatas et al. (2012) find that the consumption-oriented PMT is about ten percentage points more accurate than the CBT ($\alpha = 0.10$).

Third, our finding of the CBT's good performance in urban neighborhoods is novel. CBT initially emerged from so-called rapid rural appraisals and has so far predominantly been applied in rural settings (Chambers, 1994a). Coady et al. (2004a) expect the method to perform worse in urban sectors, where anonymity is greater and hence the information advantage of local community members smaller. Fourth, the finding that decentralized targeting is less accurate in bigger communities is in line with Alatas et al. (2012). On the other hand, in the African context considered here, the accuracy of PMTs suffers from a larger community size to a similar extent, which is in contrast to the findings of the just-mentioned study in Indonesia. While we are aware that, with an average of around 110 households, community sizes are moderate in our context, our finding makes a case for the applicability of community-based targeting beyond small villages.

Finally, findings from our cost-effectiveness calculations demonstrate the trade-off between CBT's lower program costs on the one hand and the consumption-oriented PMT's higher accuracy on the other. Even if there is much anecdotal evidence for CBT's relative cost advantage over statistical targeting methods, there are very few studies including cost data. In our context, where we consider an inexpensive decentralized expert assessment, community-based targeting is more cost-effective than any of the statistical methods. The accuracy gains of the consumption-oriented PMT outweigh the CBT's cost advantage only for very large transfer amounts. For the average transfer in our application, decentralized targeting is clearly the preferable method. But even for larger, hypothetical transfers, CBT dominates in this African context. For comparison, first, we consider the Indonesian unconditional cash transfer program investigated by Alatas et al. (2012). The program's cash transfers equal about 20 per cent of target households' budgets, which would amount to about $14 per household in Burkina Faso, a transfer amount where consumption-oriented statistical targeting is more cost effective only when data collection costs for the PMT are kept out of the picture. On the other hand, for a recently piloted conditional cash transfer program in Burkina Faso, the Nahouri Cash Transfers Pilot Project, which was conducted between 2008 and 2012 and designed to transfer about $80 per targeted household (Akresh et al., 2012), statistical targeting would be the more cost-effective choice, at least in rural areas.

7 Conclusion

While targeting accuracy assessments of specific welfare programs are numerous, there is only a small number of studies comparing alternative targeting methods within the same setting. Evidence is even scarcer when it comes to comparisons between statistical and decentralized targeting methods. In order to fill this research gap we have compared a community-based targeting intervention in Burkina Faso with various common PMTs, which we have calculated from household survey data. The outstandingly high targeting accuracy of the consumption-oriented PMT in our study makes a strong case for statistical targeting when the reduction of consumption poverty is the objective. Nonetheless, we shall close this paper with three remarks concerning decentralization of targeting that reach beyond the somewhat narrow domain of targeting accuracy.

First, our cost-effectiveness analysis has revealed that consumption-oriented targeting is excessively expensive when census data is not readily available. Given that a general census is typically not carried out more often than every ten years, targeting based on census data will become less accurate the more outdated the underlying data. Community-targeting exercises, on the other hand, may be repeated on a revolving basis at a moderate cost and in this way keep track of poverty transitions of households over time. This argument further suggests that revolving community-based targeting might be particularly suited for quickly-evolving environments. In our study area, for example, the community-based targeting exercise has been carried out three times between 2007 and 2011.

Second, the participative procedure of community-based targeting likely produces some benefits of itself. Since the inception of participatory appraisals, local control over the targeting process has been viewed as a desirable attribute of CBT, powerful enough to increase ownership and awareness, and foster institutional change (Chambers, 1994b). This view is supported by empirical evidence, which shows remarkably high approval rates by communities for decentralized targeting methods (Alatas et al., 2012; Robertson et al., 2014; Schüring, 2014). Savadogo et al. (2016) confirms this picture for our community-based targeting intervention. In a representative sample of 115 households, they find that more than 85 per cent approve of the targeting method.

Finally, it may be called into question whether consumption should be the sole targeting objective. Instead, there might be considerable value added to the targeting process when communities' concepts of poverty are taken into account. Recent empirical evidence on communities' poverty perceptions shows that communities consider more dimensions than only consumption (Alatas et al., 2012) and that their poverty concept is multidimensional (Van Campenhout, 2007). Furthermore, Kebede (2009) shows that poverty perceptions reflect local circumstances and Alderman (2002) finds that community assessments put more weight on chronic poverty. Considering the wealth criteria defined by the communities in our targeting exercise, it is striking that communities define most of the criteria in terms of capabilities such as 'Has insufficient food', 'Has nothing' or 'Is not able to solve problems by himself' (Savadogo et al., 2015). This fits well into Amartya Sen's capability approach (Sen, 1988) and supports the view that communities consider consumption rather as a 'means to an end'. In this perspective, community-based targeting appears to be well-suited for translating deprivations in the space of capabilities into targeting outcomes.

Appendix: Targeting accuracy and poverty reduction

We consider a distribution of consumption y characterized by the smooth density function $f(y)$. Now consider an anti-poverty program that relies on some targeting method. We assume that the inclusion probability of that method (equal to one minus the exclusion error), IP say, may vary along the realization of consumption, and accordingly write $IP(y)$. Then, for a given transfer per eligible household of amount t, which we assume to increase consumption by the same amount, the consumption distribution after implementation of the program is

$$f(y;t) = (1 - IP(y))\, f(y) + IP(y-t) f(y-t).$$

In words, the density at y equals the exclusion error at y times the original density at y plus the inclusion probability at $y-t$ times the original density at $y-t$. It is easily verified that $f(y;t)$ integrates to one.

Regarding poverty indices, we consider the poverty gap index (Foster et al., 1984). We write

$$P(t) = \int_0^p \frac{p-y}{p} f(y;t)dy,$$

where p is the poverty line. We evaluate poverty reduction resulting from the anti-poverty program under consideration with a small transfer amount in place by a first-order Taylor expansion, which equals t times the derivative of $P(t)$ with respect to t evaluated at t equal to zero. Straightforward calculations yield

$$\Delta P \approx -\frac{F(p)}{p} E[IP(Y)|Y \leq p]t. \tag{A1}$$

Notice that $F(p)$ equals the headcount ratio in the absence of the program, which, according to our assumptions, is equal to the share of targeted households in the population (20 percent in our application). Further, $E[IP(Y)|Y \leq p]$ is just the probability limit of the average sample inclusion probability, or one minus the exclusion error, where the latter corresponds precisely to the estimates set out in columns 2 and 5 of Table 5.

To complete the proof of the claim that, for the poverty gap index,

$$BCR(t) = \frac{|\Delta P|}{Cost} \approx \frac{1}{p}\left(1 - ExclusionError^m\right) \frac{1}{1 + (t/TC^m)^{-1}},$$

we finally notice that the program's cost per household is

$$Cost = F(p)(TC + t),$$

where TC denotes the targeting costs per eligible (or consumption-poor) household and $F(p)$ is the share of eligible households in all households.

For an untargeted program, the exclusion error is zero, and hence $IP(y) = 1$ for all $y \leq p$, which, substituted into equation A1, implies that $\Delta P \approx -F(p)t/p$. The cost per household now equals t. No fixed costs accrue because no targeting costs are incurred implying that $Cost = t$. Taken together we have that $BCR(t)$ approximately equals the constant $F(p)/p$. Notice that, by assumption, $F(p)$ equals 0.2 in our application.

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Figures and Tables

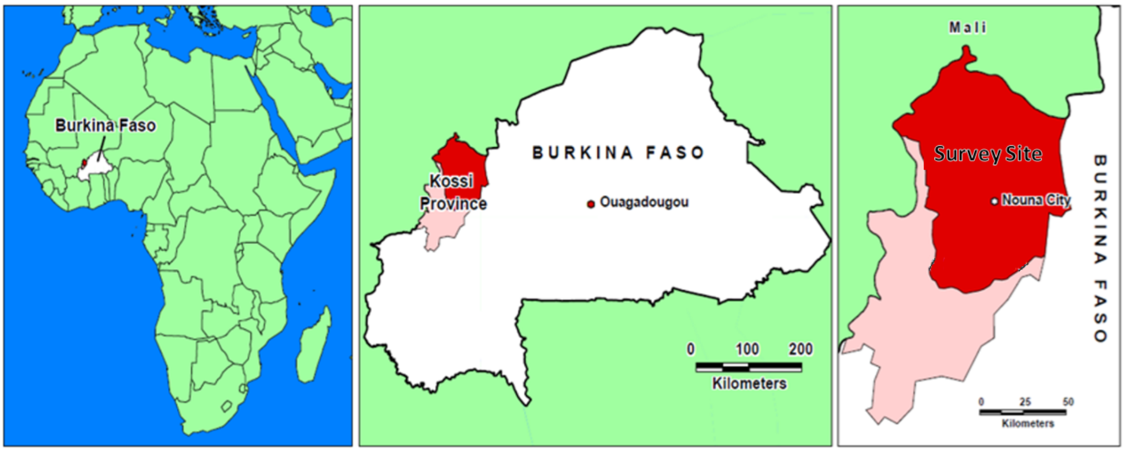

Figure 1: Location of the study site

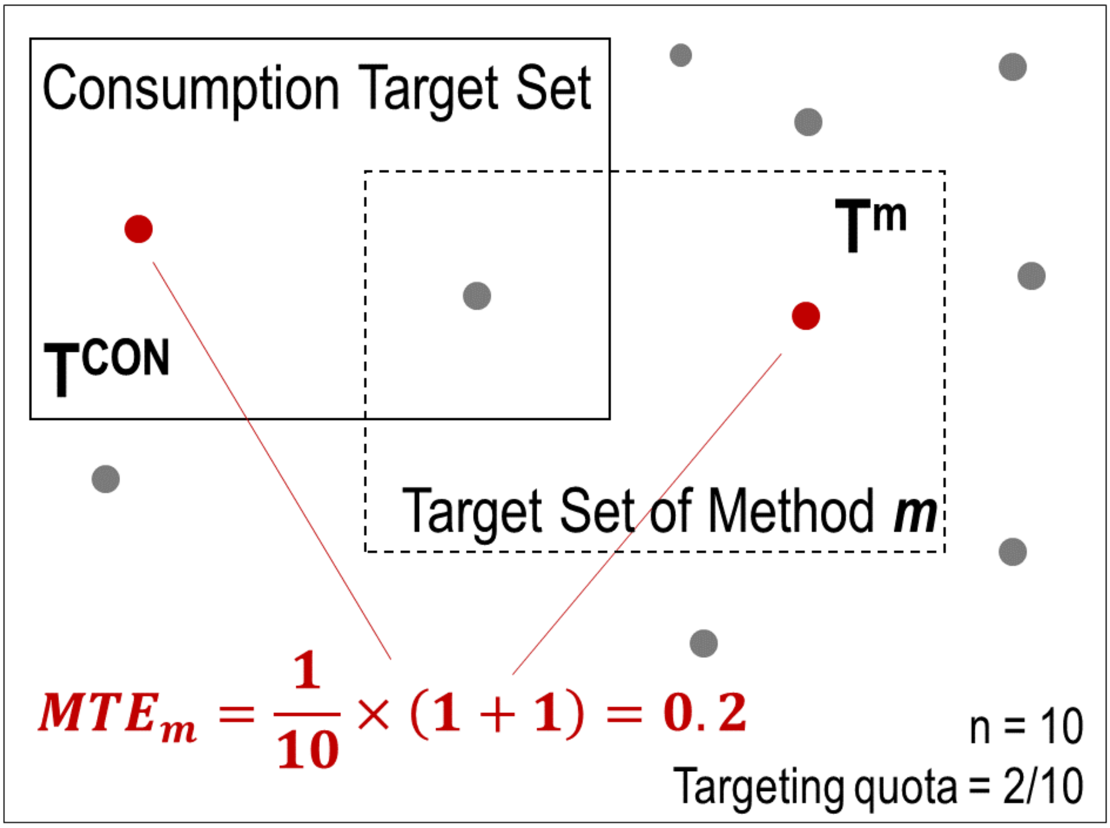

Figure 2: Calculating the mean targeting error - illustration

Table 1: Community wealth ranking procedures

Study	**Country**	**Study Population Vllg/HHs**	**Focus Group Discussions** (1)	**Wealth Brackets Y/N** (2)	**Complete Wealth Ranking Y/N** (3)	**Number of Informants** (4)
Latin America						
Takasaki et al. (2000)	Peru		*n.r.*	*n.r.*	*n.r.*	5
Karlan and Thuysbaert (2013)	Honduras	40/1,060	YES	YES	NO	*n.r.*
Karlan and Thuysbaert (2013)	Peru	40/1,007	YES	YES	NO	*n.r.*
Asia						
Adams et al. (1997)	Bangladesh	55/1,637	*n.r.*	YES	NO	5
Banerjee et al. (2007)	India	5/213	*n.r.*	YES	NO	*n.r.*
Caizhen (2010)	China	1/473	*n.r.*	YES	YES	ALL
Alatas et al. (2012)	Indonesia	640/5,753	YES	NO	YES	ALL
Sub-Saharan Africa						
Scoones (1995)	Zimbabwe	1/21	YES	YES	NO	ALL
Shaffer (1998)	Guinea	1/8	*n.r.*	YES	YES	8
Temu and Due (2000)	Tanzania	12/300	*n.r.*	YES	YES	6
Hargreaves et al. (2007)	South Africa	8/9,671	YES	YES	YES	*n.r.*
Van Campenhout (2007)	Tanzania	4/877	*n.r.*	YES	YES	1
Kebede (2009)	various	37/1,300	*n.r.*	*n.r.*	*n.r.*	*n.r.*
Souares et al. (2010)	Burkina Faso	57/910	YES	YES	YES	3
Handa et al. (2012)	Malawi	7/9,840	NO	NO	YES	5

Notes: n.r.: Not reported, *ALL*: Whole community

Table 2: Community-based targeting and community characteristics: sample means

	Rural	Urban
Community-based targeting		
Ranked households per community	116	96
Targeted households per community	23	18
Targeted households per community (share)	0.20	0.19
Targeted by all 3 informants (share)	0.08	0.08
Targeted by exactly 2 informants (share)	0.10	0.11
Targeted by exactly 1 informant (share)	0.21	0.18
Rank correlation between 3 informants	0.66	0.66
Community characteristics		
Gini (PCA-based asset index)	0.42	0.43
ELF (Ethnicity)	0.33	0.67
ELF (Religion)	0.38	0.32
Number of communities	35	22
Number of households	3721	2101

Notes: All sample means are calculated at the community level. A community is a rural village or an urban sub-sector. *ELF* is the ethno-linguistic fractionalization index and measures the probability that two randomly drawn individuals belong to different ethnic or religious groups, respectively. *Gini* is the Gini index for an asset index obtained trough principal-component analysis.

Table 3: Household survey summary statistics

	Rural	Urban
Consumption		
Monthly household head expenditures (CFA)	13,565	29,667
Demographics		
Household size	9.40	8.75
Household head literate (incidence)	0.33	0.38
HH head occup. non-agric. (incidence)	0.16	0.50
Asset possession (incidences)		
Bullock	0.50	0.40
Goat or sheep	0.83	0.60
Motorbike	0.19	0.33
Bicycle	0.91	0.94
Number of households	349	212
Share of targeted households	0.26	0.24

Notes: The sample reported here is the subset of households in the survey which also appear in the CBT. Monthly household head expenditures are based on a one month recall.

Table 4: Targeting methods

Set	Description	Number of indicators	Transformation of indicators	Weighting of indicators
Benchmark				
T^{CON}	Household head's monthly consumption expenditures (one month recall)	1	None	None
Targeting based on proxy-means testing				
Regression-based				
$T^{\widehat{CON}}$	Consumption-oriented PMT	44	None	OLS
Data-driven				
T^{PCA}	PMT based on principal-component analysis	44	None	PCA
Scorecards				
T^{PSI}	Poverty scorecard index	9	Ordered categorical	OLS
T^{BPL}	India's 'Below the Poverty Line' scorecard	12	Ordered categorical	Uniform
Counting-based				
T^{MPI}	Multi-dimensional poverty index	9	Binary	Uniform
Community-based targeting				
T^{CBT}	Households identified by three local informants			

Table 5: Mean targeting error rates

	Rural			Urban		
	(1) Mean Targeting Error	(2) Mean Exclusion Error	(3) Mean Inclusion Error	(4) Mean Targeting Error	(5) Mean Exclusion Error	(6) Mean Inclusion Error
Consumption-oriented PMT	0.15	0.30	0.10	0.10	0.22	0.07
PCA-based PMT	0.23	0.46	0.16	0.25	0.54	0.17
Scorecards						
Below the poverty line	0.28	0.54	0.18	0.24	0.50	0.15
Poverty Scorecard Index	0.35	0.69	0.23	0.35	0.74	0.23
Multidimensional Poverty Index	0.32	0.62	0.21	0.32	0.68	0.21
Community-based targeting	0.29	0.56	0.19	0.22	0.46	0.14
Random targeting error	0.38	0.74	0.26	0.36	0.76	0.24
Number of households	349	89	260	212	50	162

Table 6: Targeting error rates by consumption groups

	Targeting error rates							
	Rural				Urban			
	(1) Extremely Poor	(2) Moder. Poor	(3) Around Median	(4) Affluent	(5) Extremely Poor	(6) Moder. Poor	(7) Around Median	(8) Affluent
Dependent variable:	Exclusion Error		Inclusion Error		Exclusion Error		Inclusion Error	
Consumption-oriented PMT	0.09	0.44	0.14	0.07	0.10	0.30	0.09	0.04
PCA-based PMT	0.34	0.54	0.20	0.11	0.35	0.67	0.25	0.07
Scorecards								
Below the poverty line	0.57	0.52	0.20	0.16	0.30	0.63	0.23	0.07
Poverty Scorecard Index	0.83	0.59	0.24	0.23	0.75	0.73	0.31	0.13
Multidimensional Poverty Index	0.60	0.63	0.23	0.19	0.60	0.73	0.26	0.15
Community-based targeting	0.46	0.63	0.25	0.13	0.35	0.53	0.21	0.07
Random targeting error	0.74	0.74	0.26	0.26	0.76	0.76	0.24	0.24
Number of households	35	54	138	122	20	30	87	75

Table 7: Mean targeting error rates for alternative sets of indicators and weights

	Set of proxy-means variables			
	(1) MPI(#9)	(2) PSI(#9)	(3) BPL(#12)	(4) All(#43)
Weights				
Rural (N=349)				
Original	0.32	0.35	0.28	.
PCA	0.38	0.24	0.26	0.23
Regression-based				
Log(expd)^{OLS}	0.26	0.21	0.24	0.18
Elig(expd)^{OLS}	0.28	0.21	0.23	0.15
Urban (N=212)				
Original	0.32	0.35	0.24	.
PCA	0.40	0.29	0.24	0.25
Regression-based				
Log(expd)^{OLS}	0.26	0.23	0.22	0.16
Elig(expd)^{OLS}	0.25	0.18	0.20	0.10

Notes: The shaded cells contain mean targeting errors for the PMTs used in the main analysis. Further hypothetical PMTs are constructed by disaggregating the five existing PMTs along two dimensions; the set of indicators (columns) and the weights applied (rows). *Weights = Original* refers to the original weights used for the MPI and the two scorecards.

Table 8: Mean targeting error rates and community characteristics

	Dependent variable: Mean targeting error					
	(1)	(2)	(3)	(4)	(5)	(6)
	Consumpt.-	PCA-	Scorecards			Commun.-
	oriented	based	BPL	PSI	MPI	based
Community Size (in 100 HHs)	0.03	0.05**	0.05**	0.05*	0.05**	0.06**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Gini (PCA-Asset-Index)	0.02	0.04	0.02	-0.02	0.00	0.03
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ELF (Ethnicity)	0.06**	0.07*	0.01	0.08*	0.01	0.09**
	(0.02)	(0.04)	(0.03)	(0.05)	(0.03)	(0.04)
ELF (Religion)	-0.04*	-0.08***	-0.05**	-0.01	-0.03	-0.07**
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Rural sector (dummy variable)	0.10*	0.04	0.01	0.08	-0.02	0.13
	(0.05)	(0.08)	(0.05)	(0.10)	(0.06)	(0.08)
Constant	0.08**	0.22***	0.23***	0.27***	0.30***	0.17***
	(0.03)	(0.05)	(0.03)	(0.06)	(0.04)	(0.05)
Number of communities	57	57	57	57	57	57
F-test for joint significance	0.09	0.06	0.10	0.22	0.47	0.03
R^2	0.13	0.18	0.12	0.10	0.07	0.18

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses. For ease of interpretation all explanatory variables have been standardized.

Table 9: Cost-effectiveness analysis

Method A is more cost-effective than method B for transfer amounts smaller than		**Cost scenarios**		
		(1)	(2)	(3)
A	B	Data processing and no data collection	Data processing and consump. data collection	Data processing and full data collection
Rural				
CBT	*Consumption-PMT*	1.68	37.13	67.64
CBT	*PCA-based PMT*	0	0	78.77
PCA-based PMT	*Consumption-PMT*	3.89	74.60	56.57
Urban				
CBT	*Consumption-PMT*	2.63	49.76	90.32
CBT	*PCA-based PMT*	always	always	always
PCA-based PMT	*Consumption-PMT*	0.89	31.01	12.98

Notes: The maximum transfer for which method A is more cost-effective than method B is calculated by solving the inequality $BCR(y)^A \geq BCR(y)^B$ for y, where $BCR(y)^K$ is the benefit-to-cost-ratio of method K. PMT cost figures are based on a cost study by Lietz et al. (2015). The full data collection costs for the consumption-oriented PMT include the implementation costs of two data collection campaigns, the consumption survey and the census. Full data collection for PCA-based PMT include only the implementation costs of the census data collection campaign.

Appendix

List of Figures

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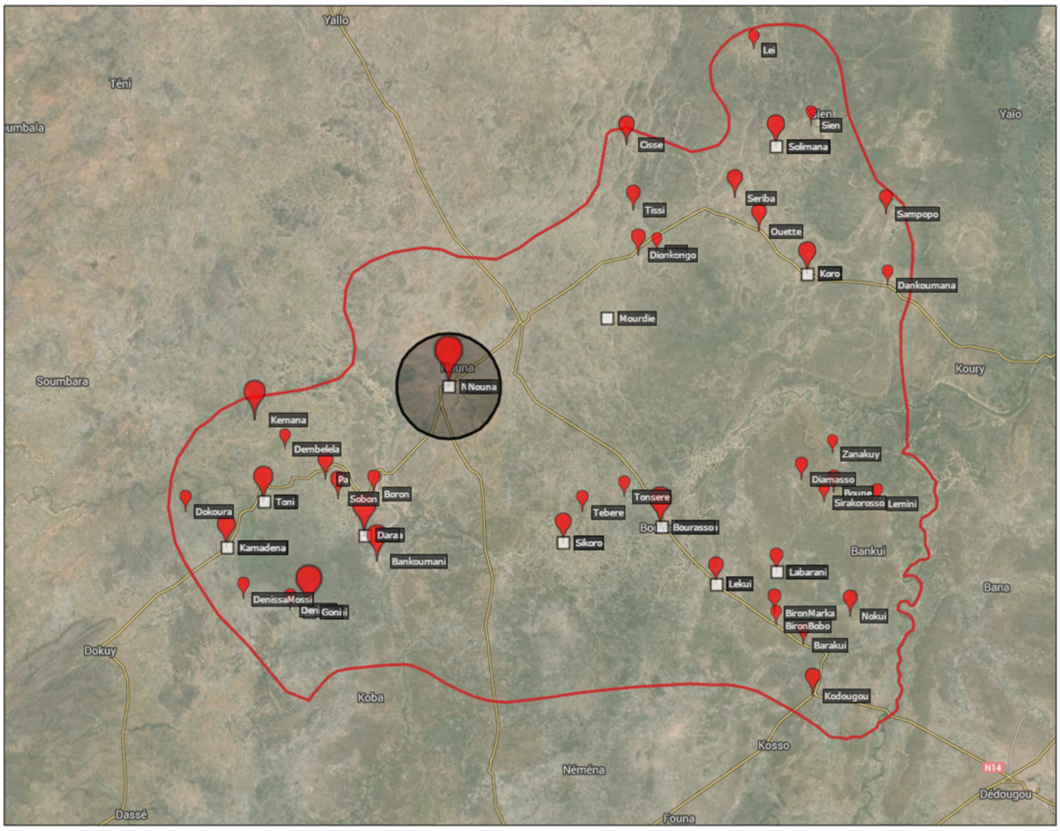

Figure A1: The survey site

Notes: Map depicts the location and population of the 41 villages. For Nouna town see Figure A2. Created with GPS Visualizer.

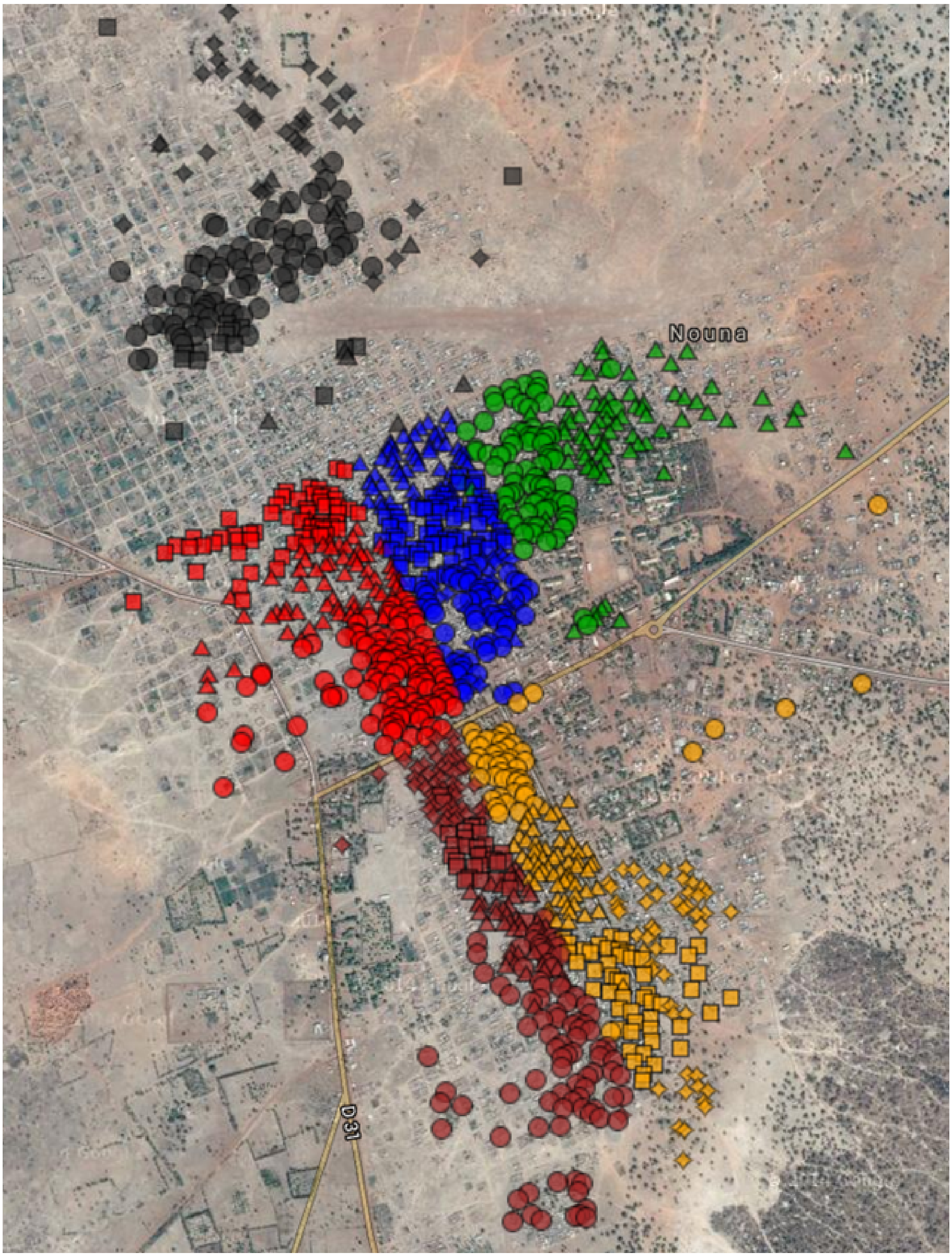

Figure A2: Nouna town and its neighborhoods

Notes: Map depicts the distribution of households across six town-sectors. The latter are depicted in different colors. Within in each sector there are two to four neighborhoods depicted by different symbols.

Table A1: Five Proxy-means test (PMT) indices and their specifications

Indicators	**Number of categories used**	**Multidim. Poverty**	**Poverty Scorecard**	**Below the pov.line**	**Principal Component**	**Consumpt.-oriented**
Total number of variables used		9	9	12	44	44
Demographic characteristics						
At least one male HH-Member at age 15	2				x	x
At least one female HH-Member at age 15	2				x	x
At least one male HH-Member at age 16 to 60	2				x	x
At least one female HH-Member at age16 to 60	2				x	x
At least one male HH-Member at age 60	2				x	x
At least one female HH-Member at age 60	2				x	x
How many household members are 15-years-old or younger?	7		x			
HHHead is married	2				x	x
HHHead is polyg married	2				x	x
HHHead is not widowed	2				x	x
HHHead is male	2				x	x
Occupational choice						
HHH can read or write	2		x		x	x
HHH response for literate	2			x	x	x
No one in the HH is literate	2	x				
Any HH member completed primary	2		x		x	x
No HH member has completed five years of schooling	2	x				
Any HH member completed secondary	2				x	x
HHH completed secondary	2				x	x
Any HH member completed tertiary	2				x	x
HHH is not employed in agriculture	2				x	x
Any HH member is not employed in agriculture	2		x		x	x
Share of employable household members	5			x		
Type of occupation (nothing, agric., non-agric.)	3			x		
Status of children (5-14 years)	3			x		
HH head is disabled	2				x	x
Dwelling characteristics						
HH uses running-water or good wells, any period	2	x			x	x
Drinking Water is changed at least every 2nd day	2				x	x
Wastewater by cesspool, gutters or septic tank	2				x	x
Water is not piped outside	2	x				
Source of drinking water	4		x			
Drinking Water arrangement	4			x		
Sanitation not at the open field	2				x	x
Toilet arrangement	3		x			
number of rooms	n.A.				x	x
Type of house	5			x		
Roof is made of concrete, metal sheets, or tile	2				x	x
Wall is not made of ordinary mud or straw	2				x	x
Floor is made of cement	2	x			x	x
Garbage evacuation through dustbin	2				x	x
No electricity or solar panel	2	x				
Main energy source of lighting	4		x			
Cooking fuel is wood	2	x				
Asset possession at household level						
At least one cart	2				x	x
At least one plow	2				x	x
At least one bike	2				x	x
At least one mbike	2		x		x	x
At least one car	2				x	x
At least one radio	2				x	x
At least one tv	2		x		x	x
At least one tel	2				x	x
At least one fridge	2				x	x
At least one kitchen	2				x	x
Ownership of 3 assets	4			x		
HH owns no assets at all	2	x				
Livestock possession at household level						
At least one horse_donkey	2				x	x
At least one goat_sheep	2				x	x
At least one chicken	2				x	x
At least one bullock	2				x	x
At least one pig	2				x	x
Number of bulocks owned by HH head	4		x	x		
Other						
HH experienced at least one severe illnes last month	2	x				
Type of risk coping	3			x		
At least one HH member emigrated last year	2			x		
Usage of transfers received	4			x		
HHs belongs to ethnic minority group	2				x	x
Relative size of primary agricultural output	5			x		

Notes: The second column *Categories* specifies the number of categories of the variable. The majority of variables consists of indicator variables which only take on two values.

Table A2: Indicators and weights of the consumption-oriented PMT index

	Dependent variable: Eligible by consumption	
	Rural	Urban
Any HH-member with primary education	-0.111	-0.155
Any HH-member with secondary education	-0.101	0.040
Any HH-member with tertiary education	0.000	0.023
Household head literate (incidence)	-0.222	-0.030
HHH response for level2	0.003	-0.086
HHH can read or write	0.147	-0.055
HH head occup. non-agric. (incidence)	0.061	0.035
Incidence of no_primagr at HH-level	-0.084	0.376
HHs belongs to ethnic minority group	0.196	-0.050
HHHead is disabled	0.033	0.134***
HH uses running-water or good wells, any period	0.015	0.078
Drinking Water is changed at least every 2nd day	-0.055	-0.053
Wastewater by cesspool, gutters or septic tank	0.021	-0.252
Garbage evacuation through dustbin	-0.064	0.171
Concrete, metal sheets, or tile	0.073	0.090
No ordinary mud or straw	-0.129	-0.143
Floor is made of cement	0.000	-0.089
Not at the open field	0.010	-0.011
Number of rooms	0.017	0.007
At least one Cart	-0.038	0.128
At least one Plow	0.017	-0.073
Bicycle	0.134	-0.107
Motorbike	0.031	-0.014
At least one Car	0.093	-0.295
At least one Radio	-0.111*	-0.080
At least one TV	-0.066	-0.194**
At least one Telephone	-0.064	0.069
At least one Fridge	-0.039	0.110
At least one Kitchen	0.000	-0.162
At least one Horse or donkey	0.067	-0.083
Goat or sheep	0.040	-0.073
At least one Chicken	-0.019	0.097
Bullock	-0.097	0.077
At least one Pig	0.061	-0.043
There is a male HH-Member at age15	-0.028	-0.102
There is a female HH-Member at age15	-0.099	0.061
There is a male HH-Member at age1660	-0.065	0.043
There is a female HH-Member at age1660	-0.104	-0.164
There is a male HH-Member at age60	0.157*	0.095
There is a female HH-Member at age60	0.118	0.018
HH head is married	0.175	-0.180
HH head is polyg married	-0.200	0.178
HH head is not widowed	-0.076	-0.288*
HH head is male	0.141	0.024
Observations	349	211
R^2	0.39	0.50
F-test (p-value)	0.00	0.00

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors clustered at the household level. Regressions include community fixed effects.

Table A3: Indicators and weights of the PCA-based PMT index

	1st principal component factor loadings	
	Rural	Urban
Any HH-member with primary education	0.181	0.267
Any HH-member with secondary education	0.107	0.182
Any HH-member with tertiary education	omitted	0.030
Household head is literate	0.155	0.134
HHH response for level2	0.108	0.091
HHH can read or write	0.154	0.125
HH head employed non-agriculturally	-0.102	-0.050
No HH member applied in agriculture	0.165	0.122
HHs belongs to ethnic minority group	-0.029	-0.033
HHHead is disabled	0.002	-0.049
HH uses running-water or good wells, any period	-0.042	0.074
Drinking Water is changed at least every 2nd day	0.002	0.111
Wastewater by cesspool, gutters or septic tank	-0.015	-0.031
Garbage evacuation through dustbin	0.011	0.045
Concrete, metal sheets, or tile	0.137	0.142
No ordinary mud or straw	0.041	0.102
Floor is made of cement	omitted	0.012
Not at the open field	0.101	0.191
Number of rooms	0.228	0.231
At least one Cart	0.258	0.199
At least one Plow	0.271	0.166
At least one Bicycle	0.170	0.215
At least one Motorbike	0.217	0.208
At least one Car	0.014	0.053
At least one Radio	0.171	0.180
At least one TV	0.164	0.219
At least one Telephone	0.168	0.260
At least one Fridge	0.053	0.047
At least one Kitchen	omitted	0.067
At least one Horse or donkey	0.257	0.206
At least one Goat or sheep	0.239	0.183
At least one Chicken	0.169	0.150
At least one Bullock	0.227	0.145
At least one Pig	0.080	0.041
There is a male HH-Member at age15	0.200	0.173
There is a female HH-Member at age15	0.215	0.185
There is a male HH-Member at age1660	0.216	0.240
There is a female HH-Member at age1660	0.204	0.255
There is a male HH-Member at age60	-0.033	-0.017
There is a female HH-Member at age60	0.035	-0.032
HH head is married	0.164	0.128
HH head is polyg married	0.168	0.130
HH head is not widowed	0.141	0.150
HH head is male	-0.094	-0.114
Observations	349	211
Number of principal components	41	44

Notes: Weights are derived from a principal component analysis where all variables are first demeaned at the community level.

Table A4: The Poverty Scorecard Index

Original scorecard for Burkina Faso		*Scorecard adjusted for our study*	
Indicator	**Score**	**Indicator**	**Score**
1. How many household members are 14-years-old or younger?		1. How many household members are 15-years-old or younger?	
A. Six or more	0	A. Six or more	0
B. Five	5	B. Five	5
C. Four	6	C. Four	6
D. Three	10	D. Three	10
E. Two	13	E. Two	13
F. One	19	F. One	19
G. None	29	G. None	29
2. In what languages can the male head/spouse read and write?		2. HH head can read and/or write	
A. None, or no male head/spous	0	A. No	0
B. French only	4	B. Yes	4
C. A non-French language (regardless of French literacy)	5		
3. Has the female head/spouse completed first grade?		3. First grade completed by HH head	
A. No	0	A. No	0
B. No female head/spouse	0		
C. Yes	9	B. Yes	9
4. What is the main source of energy for lighting?		4. What is the main source of energy for lighting?	
A. Firewood, or other	0	A. Firewood, or other	0
B. Candles, kerosene, or LPG	4	B. Candles or oil lamp	4
C. Flashlight, or batteries	5	C. Flashlight	5
D. Electricity, or solar energy	8	D. Electricity, solar panel or battery	8
5. What toilet arrangement does the household have?		5. What toilet arrangement does the household have?	
A. No toilet arrangement, or other	0	A. Open field	0
B. Non-ventilated pit latrine	4	B. Latrine	4
C. Ventilated pit latrine, or flush to a septic tank	15	C. Ventilated latrine and flush toilet	15
6. Does the household own a television?		6. Does the household own a television?	
A. No	0	A. No	0
B. Yes	10	B. Yes	10
7. Does the household own a bed or a mattress?		7. Omitted	
A. No	0		
B. Yes	3		
8. Does the household own a scooter or a motorcycle?		8. Does the household own a scooter or a motorcycle?	
A. No	0	A. No	0
B. Yes	6	B. Yes	6
9. Have any household members, in their main occupation in the last seven days, worked in agriculture, animal husbandry, fishing, or forestry?		9. Is the primary occupation of the HH head in agriculture?	
A. Yes	0	A. Yes	0
B. No	8	B. No	8
10. How many head of cattle or other large animals does the household now own?		10. How many head of bullocks does the household head now own?	
A. None, or one	0	A. None, or one	0
B. Two	2	B. Two	2
C. Three to five	3	C. Three to five	3
D. Six or more	7	D. Six or more	7

Notes: This was retrieved from the following link on September 10, 2016: `http://www.progressoutofpoverty.org/country/burkina-faso`

Table A5: The Below the Poverty Line Scorecard

Original scorecard		Score				
Indicator		**0**	**1**	**2**	**3**	**4**
1	Size group of operational holding of land	Nil	Less than 1 ha of un-irrigated land (or less than 0.5 ha of irrigated land)	1-2 ha of un-irrigated land (or 0.5-1 ha of irrigated land)	2-5 ha of un-irrigated land (or 1.0 -2.5 ha of irrigated land)	More than 5 ha of un-irrigated land (or 2.5 ha of irrigated land)
2	Type of house	Houseless	Kutcha	Semi-pucca	Pucca	Urban type
3	Average availability of normal wear clothing (per household in pieces)	Less than 2	2 or more, but less than 4	4 or more, but less than 6	6 or more, but less than 10	10 or more
4	Food security	Less than one square meal per day for a major part of the year	Normally, one square meal per day, but less than one square meal occasionally	One square meal per day throughout the year	Two square meals per day with occasional shortage	Enough food throughout the year
5	Sanitation	Open defecation	Group latrine with irregular water supply	Group latrine with regular water supply	Clean group latrine with regular water supply and regular sweeper	Private latrine
6	Ownership of consumer durables: Do you own TV, electric fan, radio, pressure cooker	Nil	Any one	Two items only	Any three or all items	All items and/or any one of a list of "luxury" items
7	Literacy status of the highest literate adult	Up to Primary (Class V)	Completed Secondary (passed class X)	Graduate/ Professional diploma	Post-graduate/ Professional graduate	Up to Primary (class V)
8	Status of the household labour force	Bonded labour	Female and child labour	Only adult females and no child labor	Adult males only	Others
9	Means of livelihood	Casual labour	Subsistence cultivation	Artisan	Salary	Others
10	Status of children (5-14 years) [any child]	Not going to school and working	Going to school and working			Going to school and not working
11	Type of indebtedness	For daily consumption purposes from informal sources	For production purpose from informal sources	For other purpose from informal sources	Borrowing only from institutional agencies	No indebtedness and possession of assets
12	Reason for migration from household	Casual work	Seasonal employment	Other forms of livelihood	Non-migrant	Other purposes
13	Preference of assistance	Wage Employment/ TPDS	Self-employment	Training and skill upgradation	Housing	Loan/subsidy of more than Rs. 1,00,000

Scorecard adjusted for our study		Score				
Indicator		**0**	**1**	**2**	**3**	**4**
1	Size group of primary agricultural output	-	Lowest quartile	Second quartile	Third quartile	Fourth quartile
2	Type of house	Round hut (traditional)	House with outside facilities	House with inside facilities	Villa	Multi-storey building
3	Omitted	-	-	-	-	-
4	Drinking water source	Surface	Ordinary well	-	Good well	Running water
5	Sanitation	Open defecation	Regular latrine	-	Ventilated latrine	Flush toilet
6	Ownership of consumer durables: Do you own radio, telephone, bike	Nil	Any one	Two items only	All three items	All items and at least one of the following items: TV, fridge, motorbike, car
7	Literacy status of the highest literate adult	Not literate	Literate	Primary school	Secondary education	Tertiary education
8	Share of employable household members	0	0 < share < 0.25	0.25 < share < 0.5	0.5 < share < 0.75	0.75 < share < 1
9	Type of occupation	No occupation	Primarily agriculture	-	-	Not primarily agriculture
10	Status of children (5-14 years) [any child]	Not going to school and working	Not going to school and doing domestic work	Not going to school and not working	-	Going to school and not working
11	Type of risk coping	Nothing	Member of a savings group	-	-	Health insurance in 2006
12	At least one household member emigrated in the last year	-	Yes	-	No	-
13	Use of transfers received	Family support	Education	-	Celebrations	No transfer received

Notes: The original scorecard is from Government of India (2002)

Table A6: The Multidimensional Poverty Index

	Original MPI		MPI adjusted for our study	
Indicator		**Weight**	**Indicator**	**Adjusted MPI Weight**
Education 0.333				
Years of Schooling	No household member has completed five years of schooling	0.167	No household member has completed five years of schooling	0.167
Child School Attendance	Any school-aged child is not attending school in years 1 to 8	0.167	No one is literate	0.167
Health 0.333				
Mortality	Any child has died in the family	0.167	Any severe-illness in the last month	0.333
Nutrition	Any adult or child for whom there is nutritional information is malnourished	0.167	-	
Standard of Living 0.333				
Electricity	The household has no electricity	0.056	The household has no electricity or solar panel	0.056
Sanitation	The households sanitation facility is not improved (according to the MDG guidelines), or it is improved but shared with other households	0.056	Water not piped outside	0.056
Water	The household does not have access to clean drinking water (according to the MDG guidelines) or clean water is more than 30 minutes walking from home.	0.056	Ordinary water source	0.056
Floor	The household has dirt, sand or dung floor	0.056	Floor is not cement	0.056
Cooking Fuel	The household cooks with dung, wood or charcoal.	0.056	Household cooks with wood	0.056
Assets	The household does not own more than one of: radio, TV, telephone, bike, motorbike or refrigerator, and does not own a car or truck.	0.056	HH owns no assets	0.056

Notes: The original MPI is from Alkire and Santos (2010)

Table A7: Mean targeting error rates, alternative consumption definition

	Rural			Urban		
	(1) Mean Targeting Error	(2) Mean Exclusion Error	(3) Mean Inclusion Error	(4) Mean Targeting Error	(5) Mean Exclusion Error	(6) Mean Inclusion Error
Consumption-oriented PMT	0.19	0.37	0.13	0.11	0.24	0.07
PCA-based PMT	0.25	0.48	0.17	0.25	0.54	0.17
Scorecards						
Below the poverty line	0.28	0.54	0.18	0.22	0.46	0.14
Poverty Scorecard Index	0.32	0.62	0.21	0.33	0.70	0.22
Multidimensional Poverty Index	0.33	0.65	0.22	0.30	0.64	0.20
Community-based targeting	0.28	0.55	0.19	0.25	0.52	0.16
Random targeting error	0.38	0.74	0.26	0.36	0.76	0.24
Number of households	349	89	260	212	50	162

Table A8: Differences between pairs of MTEs, Rural Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.03	-0.07*	-0.11**	0.03	-0.09**	-0.11***	-0.14***	-0.09**	-0.11***	-0.17***	-0.14***	-0.07*	-0.11***	-0.19***	-0.06
MPI(#7)			-0.04	-0.07*	0.06*	-0.05	-0.08**	-0.10***	-0.05	-0.07*	-0.13***	-0.11***	-0.03	-0.08**	-0.16***	-0.03
BPL(#12)				-0.03	0.10**	-0.01	-0.04	-0.06*	-0.01	-0.03	-0.09***	-0.07*	0.01	-0.04	-0.12***	0.01
PCA-based Weight																
PSI(#10)					0.14***	0.02	-0.01	-0.03	0.02	-0.00	-0.06**	-0.03*	0.04	-0.01	-0.09***	0.05
MPI(#7)						-0.11***	-0.14***	-0.17***	-0.11**	-0.14***	-0.19***	-0.17***	-0.10**	-0.14***	-0.22***	-0.09**
BPL(#12)							-0.03	-0.05	-0.00	-0.02	-0.08**	-0.06*	0.02	-0.03	-0.11***	0.02
All(#44)								-0.02	0.03	0.01	-0.05*	-0.03	0.05	-0.00	-0.08**	0.05*
Log(expd)-based Weight																
PSI(#10)									0.05*	0.03	-0.03	-0.01	0.07*	0.02	-0.06**	0.07**
MPI(#7)										-0.02	-0.08***	-0.06*	0.02	-0.03	-0.11***	0.02
BPL(#12)											-0.06*	-0.03	0.04*	-0.01	-0.09***	0.05
All(#44)												0.02	0.10***	0.05*	-0.03	0.10***
Elig(expd)-based Weight																
PSI(#10)													0.07**	0.03	-0.05*	0.08**
MPI(#7)														-0.05*	-0.13***	0.01
BPL(#12)															-0.08**	0.05*
All(#44)																0.13***
CBT																
Observations	349	349	349	349	349	349	349	349	349	349	349	349	349	349	349	349

Notes: Shaded cells contain targeting methods used in the main analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at household level.

Table A9: Differences between pairs of MTEs, Urban Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.03	-0.11**	-0.06	0.05	-0.11**	-0.09*	-0.12***	-0.08*	-0.13***	-0.19***	-0.17***	-0.09*	-0.15***	-0.25***	-0.13***
MPI(#7)			-0.08*	-0.03	0.08	-0.08*	-0.07	-0.09*	-0.06	-0.10**	-0.16***	-0.14***	-0.07	-0.12***	-0.22***	-0.10**
BPL(#12)				0.06	0.16***	0.00	0.02	-0.01	0.03	-0.02	-0.08**	-0.06	0.02	-0.04	-0.13***	-0.02
PCA-based Weight																
PSI(#10)					0.10*	-0.06	-0.04	-0.07*	-0.03	-0.08*	-0.13***	-0.11***	-0.04	-0.09**	-0.19***	-0.08*
MPI(#7)						-0.16***	-0.14**	-0.17***	-0.13**	-0.18***	-0.24***	-0.22***	-0.14**	-0.20***	-0.29***	-0.18***
BPL(#12)							0.02	-0.01	0.03	-0.02	-0.08**	-0.06	0.02	-0.04	-0.13***	-0.02
All(#44)								-0.03	0.01	-0.04	-0.09***	-0.08*	0.00	-0.06*	-0.15***	-0.04
Log(expd)-based Weight																
PSI(#10)									0.04	-0.01	-0.07*	-0.05*	0.03	-0.03	-0.12***	-0.01
MPI(#7)										-0.05	-0.10**	-0.08**	-0.01	-0.07*	-0.16***	-0.05
BPL(#12)											-0.06	-0.04	0.04	-0.02	-0.11***	0.00
All(#44)												0.02	0.09**	0.04	-0.06*	0.06*
Elig(expd)-based Weight																
PSI(#10)													0.08*	0.02	-0.08**	0.04
MPI(#7)														-0.06	-0.15***	-0.04
BPL(#12)															-0.09***	0.02
All(#44)																0.11***
CBT																
Observations	212	212	212	212	212	212	212	212	212	212	212	212	212	212	212	212

Notes: Shaded cells contain targeting methods used in the main analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at household level.

Table A10: Differences between pairs of MTEs, Extremely poor households, Rural Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.23**	-0.26*	-0.49***	-0.06	-0.34**	-0.49***	-0.57***	-0.34**	-0.46***	-0.71***	-0.60***	-0.46***	-0.46***	-0.74***	-0.37**
MPI(#7)			-0.03	-0.26*	0.17	-0.11	-0.26*	-0.34*	-0.11	-0.23	-0.49***	-0.37**	-0.23*	-0.23*	-0.51***	-0.14
BPL(#12)				-0.23*	0.20	-0.09	-0.23*	-0.31**	-0.09	-0.20*	-0.46***	-0.34**	-0.20	-0.20*	-0.49***	-0.11
PCA-based Weight																
PSI(#10)					0.43***	0.14	0.00	-0.09	0.14	0.03	-0.23**	-0.11	0.03	0.03	-0.26**	0.11
MPI(#7)						-0.29*	-0.43**	-0.51***	-0.29*	-0.40**	-0.66***	-0.54***	-0.40**	-0.40**	-0.69***	-0.31*
BPL(#12)							-0.14	-0.23*	0.00	-0.11	-0.37***	-0.26*	-0.11	-0.11	-0.40***	-0.03
All(#44)								-0.09	0.14	0.03	-0.23**	-0.11	0.03	0.03	-0.26**	0.11
Log(expd)-based Weight																
PSI(#10)									0.23*	0.11	-0.14	-0.03	0.11	0.11	-0.17*	0.20
MPI(#7)										-0.11	-0.37***	-0.26*	-0.11	-0.11	-0.40***	-0.03
BPL(#12)											-0.26**	-0.14	0.00	0.00	-0.29**	0.09
All(#44)												0.11	0.26**	0.26*	-0.03	0.34***
Elig(expd)-based Weight																
PSI(#10)													0.14	0.14	-0.14	0.23*
MPI(#7)														0.00	-0.29**	0.09
BPL(#12)															-0.29**	0.09
All(#44)																0.37***
CBT																
Observations	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35

Notes: Shaded cells contain targeting methods used in the main analysis. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors clustered at household level.

Table A11: Differences between pairs of MTEs, Moderately poor households, Rural Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		0.04	-0.07	-0.04	0.13	-0.06	-0.06	-0.07	-0.06	-0.06	-0.07	-0.07	0.07	-0.07	-0.15	0.04
MPI(#7)			-0.11	-0.07	0.09	-0.09	-0.09	-0.11	-0.09	-0.09	-0.11	-0.11	0.04	-0.11	-0.19*	0.00
BPL(#12)				0.04	0.20*	0.02	0.02	0.00	0.02	0.02	0.00	-0.00	0.15	-0.00	-0.07	0.11
PCA-based Weight																
PSI(#10)					0.17	-0.02	-0.02	-0.04	-0.02	-0.02	-0.04	-0.04	0.11	-0.04	-0.11	0.07
MPI(#7)						-0.19	-0.19	-0.20*	-0.19	-0.19	-0.20*	-0.20*	-0.06	-0.20*	-0.28**	-0.09
BPL(#12)							0.00	-0.02	0.00	0.00	-0.02	-0.02	0.13	-0.02	-0.09	0.09
All(#44)								-0.02	-0.00	0.00	-0.02	-0.02	0.13	-0.02	-0.09	0.09
Log(expd)-based Weight																
PSI(#10)									0.02	0.02	-0.00	0.00	0.15	-0.00	-0.07	0.11
MPI(#7)										-0.00	-0.02	-0.02	0.13*	-0.02	-0.09	0.09
BPL(#12)											-0.02	-0.02	0.13*	-0.02	-0.09	0.09
All(#44)												0.00	0.15	0.00	-0.07	0.11
Elig(expd)-based Weight																
PSI(#10)													0.15	0.00	-0.07	0.11
MPI(#7)														-0.15*	-0.22**	-0.04
BPL(#12)															-0.07	0.11
All(#44)																0.19*
CBT																
Observations	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54

Notes: Shaded cells contain targeting methods used in the main analysis. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors clustered at household level.

Table A12: Differences between pairs of MTEs, Around median households, Rural Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.01	-0.04	-0.03	-0.04	-0.01	-0.04	-0.07	-0.04	-0.04	-0.07	-0.06	-0.03	-0.04	-0.10*	0.01
MPI(#7)			-0.03	-0.02	-0.03	-0.01	-0.03	-0.06	-0.04	-0.03	-0.07	-0.05	-0.02	-0.04	-0.09*	0.01
BPL(#12)				0.01	0.00	0.02	0.00	-0.03	-0.01	0.00	-0.04	-0.02	0.01	-0.01	-0.07	0.04
PCA-based Weight																
PSI(#10)					-0.01	0.01	-0.01	-0.04	-0.01	-0.01	-0.04	-0.03	0.00	-0.01	-0.07	0.04
MPI(#7)						0.02	0.00	-0.03	-0.01	0.00	-0.04	-0.02	0.01	-0.01	-0.07	0.04
BPL(#12)							-0.02	-0.05	-0.03	-0.02	-0.06	-0.04	-0.01	-0.03	-0.09*	0.02
All(#44)								-0.03	-0.01	0.00	-0.04	-0.02	0.01	-0.01	-0.07	0.04
Log(expd)-based Weight																
PSI(#10)									0.02	0.03	-0.01	0.01	0.04	0.02	-0.04	0.07
MPI(#7)										0.01	-0.03	-0.01	0.01	0.00	-0.06	0.05
BPL(#12)											-0.04	-0.02	0.01	-0.01	-0.07	0.04
All(#44)												0.01	0.04	0.03	-0.03	0.08*
Elig(expd)-based Weight																
PSI(#10)													0.03	0.01	-0.04	0.07
MPI(#7)														-0.01	-0.07	0.04
BPL(#12)															-0.06	0.05
All(#44)																0.11**
CBT																
Observations	138	138	138	138	138	138	138	138	138	138	138	138	138	138	138	138

Notes: Shaded cells contain targeting methods used in the main analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at household level.

Table A13: Differences between pairs of MTEs, Affluent households, Rural Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.04	-0.07	-0.12*	0.08	-0.11*	-0.12*	-0.12*	-0.07	-0.11*	-0.16**	-0.14**	-0.07	-0.11*	-0.16***	-0.10
MPI(#7)			-0.02	-0.08	0.12*	-0.07	-0.08*	-0.08	-0.03	-0.07	-0.11**	-0.10*	-0.02	-0.07	-0.12**	-0.06
BPL(#12)				-0.06	0.15*	-0.04	-0.06	-0.06	-0.01	-0.05	-0.09**	-0.07	-0.00	-0.05	-0.10*	-0.03
PCA-based Weight																
PSI(#10)					0.20***	0.02	0.00	0.00	0.05	0.01	-0.03	-0.02	0.06	0.01	-0.04	0.02
MPI(#7)						-0.19***	-0.20***	-0.20***	-0.16**	-0.20***	-0.24***	-0.22***	-0.15**	-0.20***	-0.25***	-0.18***
BPL(#12)							-0.02	-0.02	0.03	-0.01	-0.05	-0.03	0.04	-0.01	-0.06	0.01
All(#44)								-0.00	0.05	0.01	-0.03	-0.02	0.06	0.01	-0.04	0.02
Log(expd)-based Weight																
PSI(#10)									0.05	0.01	-0.03	-0.02	0.06	0.01	-0.04	0.02
MPI(#7)										-0.04	-0.08*	-0.07*	0.01	-0.04	-0.09**	-0.02
BPL(#12)											-0.04	-0.02	0.05	-0.00	-0.05	0.02
All(#44)												0.02	0.09**	0.04	-0.01	0.06
Elig(expd)-based Weight																
PSI(#10)													0.07*	0.02	-0.02	0.04
MPI(#7)														-0.05	-0.10**	-0.03
BPL(#12)															-0.05	0.02
All(#44)																0.07*
CBT																
Observations	122	122	122	122	122	122	122	122	122	122	122	122	122	122	122	122

Notes: Shaded cells contain targeting methods used in the main analysis. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors clustered at household level.

Table A14: Differences between pairs of MTEs, Extremely poor households, Urban Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.15	-0.45**	-0.10	0.10	-0.40*	-0.40*	-0.35*	-0.30	-0.45*	-0.50**	-0.40**	-0.40*	-0.45*	-0.65***	-0.40*
MPI(#7)			-0.30*	0.05	0.25	-0.25	-0.25	-0.20	-0.15	-0.30*	-0.35**	-0.25*	-0.25	-0.30	-0.50***	-0.25
BPL(#12)				0.35*	0.55**	0.05	0.05	0.10	0.15	0.00	-0.05	0.05	0.05	0.00	-0.20*	0.05
PCA-based Weight																
PSI(#10)					0.20	-0.30*	-0.30*	-0.25*	-0.20	-0.35*	-0.40**	-0.30*	-0.30	-0.35*	-0.55***	-0.30*
MPI(#7)						-0.50**	-0.50**	-0.45**	-0.40*	-0.55**	-0.60***	-0.50**	-0.50**	-0.55**	-0.75***	-0.50**
BPL(#12)							0.00	0.05	0.10	-0.05	-0.10	0.00	0.00	-0.05	-0.25*	-0.00
All(#44)								0.05	0.10	-0.05	-0.10	0.00	0.00	-0.05	-0.25*	0.00
Log(expd)-based Weight																
PSI(#10)									0.05	-0.10	-0.15	-0.05	-0.05	-0.10	-0.30*	-0.05
MPI(#7)										-0.15	-0.20	-0.10	-0.10	-0.15	-0.35**	-0.10
BPL(#12)											-0.05	0.05	0.05	0.00	-0.20*	0.05
All(#44)												0.10	0.10	0.05	-0.15	0.10
Elig(expd)-based Weight																
PSI(#10)													0.00	-0.05	-0.25*	0.00
MPI(#7)														-0.05	-0.25	-0.00
BPL(#12)															-0.20*	0.05
All(#44)																0.25*
CBT																
Observations	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

Notes: Shaded cells contain targeting methods used in the main analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at household level.

Table A15: Differences between pairs of MTEs, Moderately poor households, Urban Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		0.00	-0.10	-0.13	0.10	-0.13	-0.07	-0.20	-0.10	-0.17	-0.33*	-0.33**	-0.07	-0.23	-0.43**	-0.20
MPI(#7)			-0.10	-0.13	0.10	-0.13	-0.07	-0.20	-0.10	-0.17	-0.33*	-0.33*	-0.07	-0.23*	-0.43***	-0.20
BPL(#12)				-0.03	0.20	-0.03	0.03	-0.10	0.00	-0.07	-0.23*	-0.23*	0.03	-0.13	-0.33***	-0.10
PCA-based Weight																
PSI(#10)					0.23	-0.00	0.07	-0.07	0.03	-0.03	-0.20	-0.20	0.07	-0.10	-0.30*	-0.07
MPI(#7)						-0.23	-0.17	-0.30*	-0.20	-0.27*	-0.43**	-0.43**	-0.17	-0.33*	-0.53***	-0.30*
BPL(#12)							0.07	-0.07	0.03	-0.03	-0.20	-0.20	0.07	-0.10	-0.30**	-0.07
All(#44)								-0.13	-0.03	-0.10	-0.27*	-0.27**	-0.00	-0.17	-0.37**	-0.13
Log(expd)-based Weight																
PSI(#10)									0.10	0.03	-0.13	-0.13*	0.13	-0.03	-0.23*	-0.00
MPI(#7)										-0.07	-0.23*	-0.23*	0.03	-0.13	-0.33**	-0.10
BPL(#12)											-0.17	-0.17	0.10	-0.07	-0.27**	-0.03
All(#44)												0.00	0.27*	0.10	-0.10	0.13
Elig(expd)-based Weight																
PSI(#10)													0.27**	0.10	-0.10	0.13
MPI(#7)														-0.17	-0.37**	-0.13
BPL(#12)															-0.20*	0.03
All(#44)																0.23
CBT																
Observations	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30

Notes: Shaded cells contain targeting methods used in the main analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at household level.

Table A16: Differences between pairs of MTEs, Around median households, Urban Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		-0.05	-0.08	-0.06	-0.17*	-0.09	-0.06	-0.11	-0.07	-0.11	-0.16**	-0.17**	-0.08	-0.13*	-0.22***	-0.10
MPI(#7)			-0.03	-0.01	-0.13*	-0.05	-0.01	-0.07	-0.02	-0.07	-0.11	-0.13*	-0.03	-0.08	-0.17**	-0.06
BPL(#12)				0.02	-0.09	-0.01	0.02	-0.03	0.01	-0.03	-0.08	-0.09	-0.00	-0.05	-0.14**	-0.02
PCA-based Weight																
PSI(#10)					-0.11	-0.03	0.00	-0.06	-0.01	-0.06	-0.10*	-0.11*	-0.02	-0.07	-0.16**	-0.05
MPI(#7)						0.08	0.11	0.06	0.10	0.06	0.01	0.00	0.09	0.05	-0.05	0.07
BPL(#12)							0.03	-0.02	0.02	-0.02	-0.07	-0.08	0.01	-0.03	-0.13**	-0.01
All(#44)								-0.06	-0.01	-0.06	-0.10*	-0.11*	-0.02	-0.07	-0.16***	-0.05
Log(expd)-based Weight																
PSI(#10)									0.05	-0.00	-0.05	-0.06	0.03	-0.01	-0.10*	0.01
MPI(#7)										-0.05	-0.09	-0.10*	-0.01	-0.06	-0.15**	-0.03
BPL(#12)											-0.05	-0.06	0.03	-0.01	-0.10*	0.01
All(#44)												-0.01	0.08	0.03	-0.06	0.06
Elig(expd)-based Weight																
PSI(#10)													0.09	0.05	-0.05	0.07
MPI(#7)														-0.05	-0.14**	-0.02
BPL(#12)															-0.09*	0.02
All(#44)																0.11*
CBT																
Observations	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87

Notes: Shaded cells contain targeting methods used in the main analysis. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors clustered at household level.

Table A17: Differences between pairs of MTEs, Affluent households, Urban Sector

	Fixed Weight			Weight based on PCA				Weight based on log(expd)-regression				Weight based on elig(expd)-regression				
	PSI (#10)	MPI (#10)	BPL (#12)	PSI (#10)	MPI (#10)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	PSI (#10)	MPI (#7)	BPL (#12)	All (#44)	CBT
Fixed Weight																
PSI(#10)		0.01	-0.07	-0.01	0.27***	-0.05	-0.07	-0.04	-0.04	-0.05	-0.08	-0.04	-0.04	-0.07	-0.09*	-0.07
MPI(#7)			-0.08	-0.03	0.25***	-0.07	-0.08	-0.05	-0.05	-0.07	-0.09	-0.05	-0.05	-0.08	-0.11*	-0.08
BPL(#12)				0.05	0.33***	0.01	0.00	0.03	0.03	0.01	-0.01	0.03	0.03	-0.00	-0.03	0.00
PCA-based Weight																
PSI(#10)					0.28***	-0.04	-0.05	-0.03	-0.03	-0.04	-0.07	-0.03	-0.03	-0.05	-0.08*	-0.05
MPI(#7)						-0.32***	-0.33***	-0.31***	-0.31***	-0.32***	-0.35***	-0.31***	-0.31***	-0.33***	-0.36***	-0.33***
BPL(#12)							-0.01	0.01	0.01	0.00	-0.03	0.01	0.01	-0.01	-0.04	-0.01
All(#44)								0.03	0.03	0.01	-0.01	0.03	0.03	0.00	-0.03	0.00
Log(expd)-based Weight																
PSI(#10)									0.00	-0.01	-0.04	0.00	0.00	-0.03	-0.05	-0.03
MPI(#7)										-0.01	-0.04	0.00	0.00	-0.03	-0.05	-0.03
BPL(#12)											-0.03	0.01	0.01	-0.01	-0.04	-0.01
All(#44)												0.04	0.04	0.01	-0.01	0.01
Elig(expd)-based Weight																
PSI(#10)													0.00	-0.03	-0.05	-0.03
MPI(#7)														-0.03	-0.05	-0.03
BPL(#12)															-0.03	0.00
All(#44)																0.03
CBT																
Observations	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75	75

Notes: Shaded cells contain targeting methods used in the main analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at household level.