Reaching the Poor: Cash Transfer Program Targeting in Cameroon

Quentin Stoeffler, University of California, Davis, qstoeffler@ucdavis.edu

Bradford Mills, Virginia Tech, bfmills@vt.edu

Carlo del Ninno, World Bank, cdelninno@worldbank.org

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Quentin Stoeffler[2], Bradford Mills[3] and Carlo del Ninno[4]

Abstract

This paper assesses the ex-post performance of two popular targeting mechanisms, Proxy Means

Testing (PMT) and Community-Based Targeting (CBT), in a pilot cash transfer program in Cameroon. CBT

is found to perform poorly in terms of selecting households with low per capita consumption when

compared to PMT. CBT appears to select households with low physical and human capital, regardless of

actual consumption level and shows more variability in the selection decision than PMT. The results

suggest caution is needed in employing CBT methods to select households with low per capita

consumption in an environment with high poverty rates and limited administrative capacity.

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1. Introduction

Effective and efficient poverty alleviation programs require accurate identification and targeting of poor

households. The increased use of direct transfers (cash, food, assets) for poverty reduction emphases

challenges faced by governments and development practitioners in terms of both identification of poor

households and generation of mechanism to deliver benefits. Beneficiary targeting is an inherently

inexact practice, with both errors of inclusion (providing benefits to households which should not be

eligible for the program) and exclusion (not providing benefits to households that should be eligible for

the program). Far from being a mere technical consideration, the choice of targeting method and

attendant targeting performance has critical implications for both the efficacy of local project

interventions and broad-based support for national social assistance policies. Thus it is not surprising

that the choice of targeting mechanism generates fierce debates among policy makers, civilian

stakeholders, and academics (Coady, Grosh, & Hoddinott, 2004; Grosh, Del Ninno, Tesliuc, & Ouerghi,

2008; Mkandawire, 2005).

The two most common methods for social safety nets targeting in Sub-Saharan Africa are proxy means

test (PMT) and community based targeting (CBT) (Del Ninno & Mills, 2014; Monchuk, 2013; Slater &

Farrington, 2009). PMT relies on statistical methods to generate a robust predictor of household

wellbeing (usually consumption). CBT relies on community participation to identify poor households.

Theoretical and empirical work is available to inform the choice and design of targeting method (Besley

& Kanbur, 1990; Van de Walle & Nead, 1995). However the literature is not conclusive regarding what

method works best in specific situations (Coady et al., 2004).

PMT implementation usually has two distinct steps. First, a PMT formula is designed from nationally

representative datasets where household characteristics (such as household size, roof material, number

of animals) are used as weights (through regression-based analyses) as predictors of household welfare.

Second, a short survey based on PMT weight variables is administered to potential beneficiaries to compute their PMT score and determine program eligibility. There are a number of stated advantages to the PMT method: i) PMT is relatively cheap and simple to implement because it is based on a data collection for a limited set of characteristics that are easy to observe and verify; ii) PMT relies on "objective" criteria, which implies credibility, fairness and robustness to manipulation in targeting decisions; iii) PMT is based on indicators (usually assets) correlated with long-term well-being rather than short-term consumption, making it particularly suited for identifying chronic poverty; iv) Because indicators are usually observable assets, PMTs often generate less disincentives to increase income, consumption or work participation than other targeting methods. However, targeting errors embodied in PMT targeting design and in PMT process corruption have been observed (Kidd & Wylde, 2011; Niehaus & Atanassova, 2013). Simple ex-ante arithmetic simulations of PMT targeting formulas suggest inclusion and exclusion errors are usually above 20% (Ahmed & Bouis, 2002; Grosh & Baker, 1995; Leite, Stoeffler, & Kryeziu, 2015; Narayan & Yoshida, 2005; Sharif, 2009). Opponents to PMT targeting often point to embodied errors, implementation issues, and exclusion of the community from the targeting process (Kidd & Wylde, 2011).

Community based targeting overcomes some of the weaknesses of PMT targeting and has been widely used in Sub-Saharan Africa (Garcia & Moore, 2012). CBT involves communities in a participatory process to select beneficiary households at the local level. Usually, a detailed process is designed by program managers where community elite meet in a village assembly and construct a list of poor households which will be beneficiaries of the program. The process also involves checks and balances to limit clientelism and elite capture. Thus, community targeting has the advantage of: i) including more *information* from the community, compared to a "blind" formula or criteria (Alderman, 2002); ii) involving the community in a participatory process, which helps generate program support; iii)

increasing transparency of selection decisions among potential beneficiaries.[5] However, elite capture, community tensions, clientelism and other implementation issues are inherent to CBT in practice (Conning & Kevane, 2002; Mansuri & Rao, 2004; Olivier de Sardan, 2013; Platteau, 2004).[6]

Careful study of targeting performance is warranted to make informed decisions on the choice of targeting methods. Recent empirical studies of targeting at the micro-level to suggest CBT targeting in Sub-Saharan Africa is mildly progressive (Handa et al., 2012; Sabates-Wheeler, Hurrell, & Devereux, 2014; Schüring, 2014). Ex-post analyses of PMT targeting reached similar conclusions (Maluccio, 2009; McBride, 2014). When PMT and CBT are compared, most studies do not find that one method clearly dominates (Banerjee, Duflo, Chattopadhyay, & Shapiro, 2007; Karlan & Thuysbaert, 2013). In particular, CBT tends to select older and smaller households, and, despite slightly lower efficiency, generates higher satisfaction in project areas than PMT targeting (Alatas, Banerjee, Hanna, Olken, & Tobias, 2012; Pop, 2014).

This paper contributes to the emerging literature on social safety net (SSN) targeting by examining the relative ex-post performance of PMT and CBT in a cash transfer project implemented by the government of Cameroon in a very poor rural region in the North of the country. The performance of separate PMT and CBT targeting mechanisms employed by the project are assessed and systematic differences are identified in terms of inclusion and exclusion errors. The analysis has several unique features compared to previous analyses. Both PMT and CBT targeting are fully employed in an actual SSN project to

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[5] In programs using PMT targeting, the targeting process is not always understood locally (Adato & Roopnaraine, 2004). Potential beneficiaries sometimes perceive that the selection list comes "from the computer" and that "the computer" randomly selects beneficiaries – so that the beneficiaries are "lucky" and the non-beneficiaries are not.
[6] Some have pointed out targeting inaccuracy and inefficiency, public and private mistargeting costs, and the negative institutional, political economy and philosophical implications of targeting (Cameron & Shah, 2014; Ellis, 2012; Mkandawire, 2005; Sen, 1995). While universal transfers may be preferred, there are budgetary and political arguments against universalism (Del Ninno & Mills, 2014; Ferguson, 2013). Alternative critics suggest targeting indicators should focus on poverty alleviation outcomes rather than *targeting* efficiency (Ravallion, 2009). However, such outcomes are usually studied through *impact* evaluations of targeted programs (Stoeffler & Mills, 2014).

determine beneficiaries among each of the 2,084 households surveyed. Household well-being

(consumption) is actually observed in a new project baseline survey, and the PMT questionnaire module

is identical to that in the national survey from which the PMT is constructed.[7] In addition, a gap in

project implementation allows assessment of medium-term targeting performance without shifts in

well-being due to project impact. The evaluation of targeting performance first uses popular targeting

efficiency indicators (i.e. inclusion and exclusion errors). New indices and non-parametric methods are

also employed to study the distribution of consumption levels and simulate poverty impacts of cash

transfers under CBT and PMT selection. Second, household characteristics associated with exclusion and

inclusion errors under the two methods are identified econometrically. The role that other information

such as exposure to shocks (known by the community but not the PMT) has on community choice is also

explored. Third, the potential for integration of PMT and CBT methods to further increase targeting

performance is examined.

Results suggest that the PMT performs slightly better than CBT in identifying households with low per

capita consumption. Compared to PMT selection, community choice seems to be driven by different

factors associated with poverty like human and physical capital asset holding. Divergence between

community and PMT targeting suggests strong complementarities between the two methods, but these

complementarities are not observed to result in better targeting performance of hybrid CBT-PMT

targeting methods than the PMT alone.

The next section describes the project and the data used in the analysis. Section three introduces the

targeting indicators employed and the empirical approach. Section four presents results, and the last

section discusses policy implications and concludes.

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[7] Survey implementation is also conducted by the same institution (Institut National de la Statistique). Evaluation of the PMT efficiency on a different dataset from the one which is used to construct the PMT is of particular importance for several reasons, including i) the difference in time between design and actual implementation of the PMT may cause predictors to lose their predictive power; ii) the ex-ante PMT performance results may be too "optimistic" because the PMT formula is fine-tuned to fit the sample from which it is generated.

2. Project description and data

A. Project and targeting

High poverty rates and the lack of adequate Social Safety Net (SSN) programs prompted the Government of Cameroon in December 2013 to launch pilot unconditional cash transfer (UCT) programs under the Social Safety Nets Pilot Project (SSNPP) that were specifically targeted to the poor. Crucial to project success in delivering cash transfer to the country's poorest households is a scalable and cost-effective targeting mechanism. Several ex-ante studies of potential targeting performance in Cameroon suggest that geographic and Proxy Means Testing (PMT) methods can effectively reach poor households (Stoeffler, Nguetse-Tegoum, & Mills, 2015; World Bank, 2011a). However, Community-Based Targeting (CBT) methods have also been commonly used in other settings in Sub-Saharan Africa to effectively target the poor households (Handa et al., 2012). SSNPP employs a hybrid targeting method which combines independently completed PMT and CBT, thus allowing a direct comparison of the performance of the two popular targeting methods.

Cameroon has seen robust recent economic growth, but poverty has remained persistently high: 40.2% of the population in 2001 and 39.9% in 2007 (World Bank, 2011a). Chronic poverty has been estimated at 26.1% and is concentrated in the rural and northern regions of Cameroon. Social assistance has been mostly *ad hoc*, lacking coordination and with low coverage. Government support has been limited until recently, as SSNs accounted for only 0.23% of GDP excluding subsidies (World Bank, 2011b).

SSNPP provides beneficiary households with 15,000 FCFA a month on average. This amount represents about 20% of average poor household consumption expenditures (Nguetse-Tegoum & Stoeffler, 2012). As noted, in order to focus on the poorest households in Cameroon while testing different targeting methods, the SSNPP combined PMT and CBT in beneficiary selection. Geographic targeting was also employed in the project design to choose Soulédé-Roua (in the Extreme-North region) which is the

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poorest *arrondissement* in the country, as the project area. The poorest 15 villages in Soulédé-Roua were then chosen in a consultation involving community leaders and project officials. About 1,500 households (35% of the population) were subsequently selected by both the PMT and CBT and designated as the "beneficiary" population. This paper focuses on performance of the two targeting methods in these 15 villages when the eligibility status of each household is evaluated by PMT and by CBT separately.

Community targeting followed a rigorous process set up by the SSNPP Project Management Unit. Local Targeting Groups (GLC) were created in each village, and to avoid conflict of interest GLC members could not be project beneficiaries. Forums and workshops were organized to discuss the definition of poverty. Criteria defining poverty, as described during these forums, include infrastructures (access to clean water, roads, etc.), housing condition, physical assets, health, education and economic activities of the village households, geographic access, agricultural land and population density. The GLCs produce lists of eligible (poor) households, and their work is checked by Citizen Control Groups (GLCC). At the *arrondissement* level (Soulédé-Roua), a *Commune* Working Group (GTC) records complains from the GLCC, manages the community targeting list and transfers it to the Project Management Unit.

The community had to select (approximately) 70% of the village households as poor, while the PMT threshold was adjusted so that 35% of the households would be beneficiaries of the SSNPP. PMT score threshold is common across villages, consequently the percentage of beneficiaries varies by village. It is also important to note that the selection target of 70% of households per village was not followed by GLCs in practice, and that actual selection rates range from 26% to 100% of the village households, depending on the village.[8]

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[8] Community ranking of households rather than dividing them in two discrete categories (selected or not as poor) would be desirable. However, the pilot project did not require the community to conduct a time-consuming

The PMT formula used in the SSNPP was generated using a nationally representative dataset collected in 2007, the *Enquete Camerounaise Aupres des Menages 3* (ECAM 3). The variables used in the PMT formula include household characteristics, housing conditions and assets that are long-term determinants and correlates of poverty along multiple dimensions. The formula generates a score which corresponds to the probability that a household is chronically poor, so that a higher score represents a higher predicted level of poverty (Nguetse-Tegoum & Stoeffler, 2012; Stoeffler, Nguetse-Tegoum, et al., 2015). The PMT score eligibility threshold is then adjusted to obtain the desired number of beneficiaries for the project.

B. Data

The analysis in this paper relies on two sources of data. For the population of 5,471 households in the 15 beneficiary villages, PMT data was collected in December 2012 in a short survey that contained only the variables needed to compute the household PMT scores. CBT was implemented at the same time for all households, but no data was recorded beyond eligibility status. The second data source is a baseline survey for future impact evaluation, collected in December 2013 among 2,084 households in Soulédé-Roua, just before the first cash transfer payment.[9] The baseline survey sample was stratified based on the PMT/community survey in order to include 828 beneficiaries, 628 non-beneficiaries chosen by CBT and 628 other non-beneficiaries. 1,758 usable observations are retrieved for the analysis and sample weights are employed to account for the stratification of the population. The baseline survey includes several modules on household demographics, education, health, economic activities, anthropometry, housing conditions, physical assets, shocks, food security, micro-enterprises and agriculture. In addition, a consumption module is used to create the main welfare measure: household aggregate per capita

exhaustive ranking. Decay in accuracy of rankings has been observed to occur with the duration spent on the task (Alatas et al., 2012).

[9] The temporal gap between the PMT survey and the baseline survey 12 months later was not intended, but is useful to study targeting efficiency in the medium-term, allowing for short-term negative or positive shocks which occurred between when targeting was conducted and the program began.

consumption. The consumption module is identical to the one included in the nationally representative survey (ECAM 3) employed to design the PMT formula, ensuring comparability with previous poverty analyses and between ex-ante and ex-post results. Unfortunately, the survey (designed primarily for the impact evaluation) does not include information on household satisfaction with the targeting process or outcomes.

Survey descriptive statistics indicate that in the sample, 720 households (42%) are selected by both the community and the PMT, 117 households (7%) are selected by neither, 443 households (26%) households are selected by the community only, and the same number (443 households or 26%) are selected by the PMT only (Table 1). Household characteristics for the whole sample and by targeting group are presented in Table 2. Overall, 54% of Soulédé-Roua *individuals* are selected by the community, and 34% are beneficiaries of the project (hybrid targeting).[10] Households are large (7.5 members on average) and male-headed (80%) on average. Most household heads went to primary school (60%) and are either Christians (42%) or Animists (41%). Household exposure to shocks is frequent, with most households affected during the last 12 months (69%). Most households have livestock (78%), with 0.73 Tropical Livestock Units (TLU) on average (about one cow).[11] Land is scarce with households cultivating 0.88 ha on average and more than half of the households renting land (51%). Most individuals live in households without any physical assets (71%) and know either moderate (39%) or severe (18%) hunger according to the Household Hunger Score (HHS). Overall, most households in Soulédé-Roua seem to experience important deprivations. Further, no clear differences appear between different targeting groups in terms of household characteristics, suggesting that a more controlled evaluation of targeting performance is needed.

C. Comparing across targeting methods

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[10] Here household size weights are used to account for the number of individuals. Sample weights are used as well.
[11] The TLU formula is: $TLU = 0.7 * cows + 0.01 * chicken + 0.1 * (sheeps + goats + rabits + dogs + other\ poultry) + 0.2 * pigs + 0.4 * equines$

The main welfare indicator used in the analysis is the per capita aggregate value of consumption.[12] The consumption aggregate is constructed by imputing on an annual basis household spending from: i) "retrospective spending" collected for the last 3, 6 or 12 months on clothes, furniture, travels, ceremonies, etc. and ii) short-term spending (last 7 days) on consumption of food and drinks (including self-produced food). Alternative consumption aggregates are tested (e.g. excluding spending on health and funerals) along with different "per consumption units" (i.e. employing an adult equivalent deflator) as robustness tests. A household is defined as poor if its per capita consumption is below a given poverty threshold. The poverty threshold is moved to reflect different rates of poverty corresponding to the inclusion rates of selection employed with CBT and PMT, for comparison of methods.

The CBT global inclusion rate is 67% in the sample.[13] However, CBT can also be assessed with village specific rates of inclusion (see 2.A). Hybrid targeting (representing the intersection of PMT and CBT) used in the SSNPP has a 35% inclusion rate and can also be assessed with a global or a village specific threshold. The PMT targeting inclusion rate, on the other hand, can be set at any level by moving the PMT threshold for the analysis since PMT scores generate a household ranking.[14] Based on these, several comparison scenarios are employed (Table 3). CBT and PMT are compared by setting CBT, PMT and poverty rates at the CBT global level (67%) or the village specific level corresponding to CBT selection. Hybrid targeting and PMT are compared by setting hybrid targeting, PMT and poverty rates at the hybrid targeting global level (35%) or the specific village level corresponding to hybrid selection. Global and village thresholds have different justifications. From a project perspective it is important to understand overall targeting performance at the global level to know if the poorest households across

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[12] There is wide recognition that poverty is multidimensional (Alkire & Foster, 2011; Sen, 1999; Stoeffler, Alwang, Mills, & Taruvinga, 2015). We focus on consumption-based poverty in this paper, partly because the PMT variables and variables used to construct a multidimensional poverty (MDP) index overlap. Measures of MDP are used as robustness checks (see section 4.C).
[13] This corresponds to targeting 58% of the households using sample weights and 54% of the *individuals* in the sample using household size and sample weights.
[14] In the SSNPP, the PMT threshold was adjusted in ordered to obtain the desired 35% inclusion rate.

villages have been reached. However given the project implementation gap that results in different shares of beneficiary households in each village, it is also important to understand if the poorest households were chosen in each village.[15]

When comparing CBT and PMT based targeting methods in each scenario, we also evaluate four other hypothetical targeting methods: i) perfect targeting; ii) random targeting; iii) universal targeting; and iv) an alternative PMT formula. Perfect targeting is the ideal objective of each targeting method, selecting all poor and only poor households (perfect inclusion and exclusion). Random targeting is the reference point of what would happen if the households were randomly selected (note that targeting methods can be regressive and perform worse than random selection). Universal targeting includes all households, so that exclusion errors do not exist. Finally, the alternative PMT formula employed is generated from the ECAM 3 survey in a similar fashion to the PMT formula used in the pilot project, but with two distinct features: i) it is generated using only observations in the Extreme-North region, making it potentially suitable to the particular context of the pilot project; and ii) it is much shorter, relying on a smaller number of variables, which makes data collection easier.[16] These fictional (perfect) and possible (random, universal and alternative PMT) targeting methods also allow meaningful comparisons in terms of expected poverty reduction. The budget of universal targeting transfers is adjusted (each household transfer is reduced) so that it is fully comparable (in terms of cost-effectiveness of poverty reduction) with the budget allocation associated with PMT and community targeting (when comparing PMT and community), or with PMT and hybrid targeting (when comparing PMT and hybrid targeting).[17]

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[15] There is an implementation "gap" because the situation *de facto* does not correspond exactly to project guidance in terms of 70% selection of village households. However, if the different levels of inclusion reflect different levels of poverty in each village, this gap may result in a greater targeting efficiency.

[16] The potential of regional and/or shorter PMT formulas is an important issue for practitioners. Nationally representative surveys have a limited number of observations at the regional level leaving a tradeoff between better fit to local conditions and fewer observations with which to fit the model.

[17] Note that without this adjustment, the poverty reduction of universal targeting with full household transfers (15,000 FCFA) is the same as the poverty reduction with perfect targeting. Indeed, all poor households receive

3. Methods

This section presents the indicators employed to assess targeting performance and the statistical methods used to identify differences in the characteristics of those experiencing exclusion and inclusion errors under PMT and CBT targeting.

A. Targeting Efficiency Indicators

Targeting measures assess two types of errors: exclusion errors or undercoverage (poor households incorrectly excluded by the program) and inclusion errors or leakages (non-poor households receiving benefits). Both errors are detrimental to the policy objective of social assistance programs (Cameron & Shah, 2014; Cornia & Stewart, 1993). An exclusion error index measures the share of poor non-beneficiaries (E2) over the total number of poor (P): $EE = \frac{E2}{P}$ (Table 4). Similarly, an inclusion error index measures the share of non-poor beneficiaries (E1) over the total number of beneficiaries (B): $IE = \frac{E1}{B}$. It is then possible to compare targeting efficiency for a given method j (IE_j and EE_j) with an alternative method k (IE_k and EE_k). Given the number of non-poor (NP), the number of non-beneficiaries (NB) and the total population (T), for random targeting $E(IE_r) = \frac{NP}{T}$ and $E(EE_r) = \frac{NB}{T}$. For universal targeting, $E(IE_r) = \frac{NP}{T}$ and $E(EE_r) = 0$.

Inclusion and exclusion errors can be synthetized in a slightly different manner with a single index called the Targeting Differential (TD), which represents the difference between the share of the poor and the non-poor participating to the program (Galasso & Ravallion, 2005): $TD = \frac{C1}{P} - \frac{E1}{NP}$ where $C1$ are the poor correctly targeted by the program, P all poor, $E1$ the non-poor erroneously included by the program, and NP all the non-poor. Thus, TD ranges between -1 and 1 with $E(TD) = 0$ when targeting

transfers with both universal and perfect targeting. However, project budget (costs) would naturally be much higher with universal targeting and full transfers.

is either random or universal, and $E(TD) = 1$ with perfect targeting. Another popular index employed

to synthetize inclusion and exclusion errors in evaluating a targeting mechanism is the share of

resources actually transferred to the poor. The CGH index (Coady et al., 2004) measures the amount of

resources transferred to the poor over the total amount transferred by the program. It is then divided

(normalized) by the share of the poor in the total population. For the x poorest percent of the

population: $CGH_x = \frac{AP}{TA} / \frac{x}{100}$ where AP is the amount transferred to the poor, TA is the total amount

transferred by the program, and x is the percentile chosen. CGH_x lies between 0 (if all resources are

transferred to the non-poor) and $\frac{100}{x}$ when all resources are transferred to the poor. $E(CGH_x) = 1$ in

case of universal or random targeting. [18]

All these targeting indices are based on a basic classification of households as poor or non-poor. As such,

they are a simplification of targeting efficiency in that they do not consider how far from the poverty

threshold selected and non-selected households lie (Slater & Farrington, 2009). For instance, similarly to

the poverty headcount, the TD index is the same if a given household i is just below the poverty line

(not very poor) or very far below the poverty line (extremely poor). For that reason, we also employ a

new Foster-Greer-Thorbecke type of index TD_α which extends the simple TD by taking into account

distance from the poverty threshold. For a given targeting mechanism j:

$$TD_{\alpha,j} = \frac{\sum_i P_{i \in J} * \left\{ \left| \frac{z - c_i}{z} \right| \right\}^\alpha}{\sum_i P_i} - \frac{\sum_i NP_{i \in J} * \left\{ \left| \frac{z - c_i}{z} \right| \right\}^\alpha}{\sum_i NP_i}$$

Where α is the power to which the gap to the threshold is raised, P_i is an indicator when i is a poor

household, NP_i is an indicator when i is not poor, $i \in J$ when i is targeted by mechanism j, z is the

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[18] CGH index does not make meaningful comparisons between programs with different targets: CGH_{35} is appropriate for a targeting method selecting 35% of the households, but it does not make sense to use the CGH_{35} for another targeting method selecting 67% of the population. The maximum value of CGH_{67} is 1.4 whereas it is 2.8 for CGH_{35}.

poverty threshold used, c_i is household's i per capita consumption. When $\propto = 0$, TD_0 incidence is the TD index proposed by Galasso and Ravallion (2005).

The $TD_\propto$ index can also be decomposed into its 2 components to show if a targeting mechanism is efficient (inefficient) because of its inclusion of poor (non-poor) households or because of its exclusion of non-poor (poor) households:

$$TD_{\propto,j,poor} = \sum_i \frac{P_{i \in J} * \left\{ \left| \frac{z - c_i}{z} \right| \right\}^\propto}{P_i}$$

$$TD_{\propto,j,non-poor} = \sum_i \frac{NP_{i \in J} * \left\{ \left| \frac{z - c_i}{z} \right| \right\}^\propto}{NP_i}$$

Another approach to analyze the distribution of selected and non-selected households' consumption levels under different targeting methods is to use nonparametric techniques. In particular for a targeting method j, the cumulative distribution functions of the log of per capita consumption is compared between non-beneficiaries and beneficiaries. The cumulative distribution function allows us to observe on which part of the distribution (poorest or wealthiest households) targeting performs better for a given method. In addition, two method j and k can be compared through cumulative distribution functions, where stochastic dominance indicates that one method performs better across all levels of consumption for instance.

Finally, the efficiency of each targeting method is assessed in terms of its potential impact on poverty reduction. For this, the impact of transfers to households selected by each targeted method are simulated by adding the transfers to their actual (pre-transfer) expenditures. The difference between pre-transfer and new poverty indices is computed for Foster-Greer-Thorbecke (FGT) (1984) poverty indices:

$$FGT^{\alpha}{}_i \; REDUCTION = FGT^{\alpha}{}_i \; SIMULATED - FGT^{\alpha}{}_i \; OBSERVED \qquad (1)$$

where i is a particular targeting method and $\alpha = 0,1,2$ for poverty incidence, gap and severity. The index measures how well poor individuals are identified and how targeting efficiency gaps may translate into differences in terms of expected poverty reduction. The simulated impact on poverty gap and severity ($\alpha = 1,2$) indicate how effectively each method reaches the poorest households (far below the poverty threshold).

B. Determinants of targeting errors

Statistical models are used to further explore systematic differences between PMT and CBT targeting and the characteristics associated with exclusion and inclusion errors of under each method. Drivers of community targeting and sources of mismatch between PMT and CBT targeting are also examined.

First, a statistical model estimates the probabilities of poor households being wrongly excluded by CBT and PMT targeting and the probabilities of non-poor households being wrongly included. A simple probit model is specified to measure the household characteristics associated with exclusion, where for household i exclusion error is defined as $ee_i = 1$ when i is poor but i is not targeted by mechanism j (community or PMT). The model is:

$$\mathrm{E}\big(ee_{ij} = 1 | \mathbf{X_i}\big) = \Phi\big(\boldsymbol{\beta_j}\mathbf{X_i} + \varepsilon_{ij}\big), \quad i \in P \qquad (2)$$

where $\mathbf{X_i}$ is a vector of household characteristics which can influence or be associated with being erroneously excluded by mechanism j and P is the set of poor households. In alternative specifications $\mathbf{X_i}$ includes controls such as log of per capita consumption aggregate, or PMT score, or both, in order to identify factors influencing targeting after taking into account household poverty status depth (in terms of per capita consumption or in terms of PMT score). The global threshold of 67% is used in this specification to compare community and PMT targeting.

A similar model is constructed for inclusion errors, where for household i inclusion error is defined as $ie_i = 1$ when i is not poor but i is targeted by mechanism j (community or PMT). The model is:

$$\Pr(ie_{ij} = 1|\mathbf{X_i}) = \Phi(\boldsymbol{\beta_j}\mathbf{X_i} + \varepsilon_{ij}), \quad i \in NP \tag{3}$$

where NP is the set of non-poor households.[19]

Second, drivers of community targeting are estimated for all poor and non-poor households to determine how household characteristics are associated with being selected by the community using a probit model. If $s_i = 1$ when household i is selected by the community:

$$\Pr(s_i = 1|\mathbf{X_i}) = \Phi(\boldsymbol{\beta}\mathbf{X_i} + \varepsilon_i), \quad i \in A \tag{4}$$

where $\mathbf{X_i}$ is a similar vector of household characteristics which can influence or be associated with being targeting by community targeting, and A is the set of all households. Again controls such as log of per capita consumption aggregate or PMT score (or both) are used in some specifications.

Thirdly, a multinomial logit model is specified to identify characteristics associated with the mismatch between community and PMT targeting through assignment to four different, mutually exclusive targeting outcomes: i) being selected by community and PMT targeting; ii) being selected by the PMT, not the community; iii) being selected by the community, not the PMT; iv) being selected by neither the community nor the PMT. The model base category is being selected by community and PMT targeting (i), consequently the coefficients indicates a departure from having the two targeting methods agreeing that a household is poor. For household i, $t_i = j$ when i's targeting status is assigned to j, and $j = 1,2,3,4$ (one of the four categories described above):

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[19] Studying inclusion errors also inform the process of exclusion, because a given household characteristic can either increase inclusion *per se* (reduce exclusion errors and increase inclusion errors), increase exclusion *per se* (increase exclusion errors and reduce inclusion errors), or actually improve targeting efficiency (reduce both types of errors).

$$\Pr(t_i = j | \mathbf{X}_i) = f(\boldsymbol{\beta}_j \mathbf{X}_i + \varepsilon_i) = \frac{\exp(\boldsymbol{\beta}_j \mathbf{X}_i)}{\sum_{l=1}^{4} \exp(\boldsymbol{\beta}_l \mathbf{X}_i)}, \qquad i \in A \tag{5}$$

where $\mathbf{X}_i$ is the same vector of household characteristics which can be associated with a targeting outcome j.

In all models, errors are clustered at the village level to take into account potential village targeting committee effects and other village effects.

4. Results

A. Targeting Assessment

Table 5 provides a comparison of community and PMT targeting by providing inclusion and exclusion errors as well as, Targeting Differential (TD), CGH index (CGH_{67}) and simulated poverty reduction measures. The PMT and per capita poverty thresholds employed identify 67% of the households as poor (similarly to community targeting) at the global level (see section 2.C). Results indicate a poor performance of community targeting *per se*, with particularly high inclusion and exclusion errors of 25.9% and 47.0% overall respectively. These errors are higher than those from random targeting. The TD is negative, indicating that non-poor households have a higher probability to be selected than poor households, and the CGH index is below 1, which means that more resources are transferred to the non-poor. Community targeting TD_1 and TD_2 are also below or about at the level of random targeting. PMT targeting performs better, with lower exclusion errors (16.7%) and inclusion errors (21.0%). However the TD and CGH indices (0.163 and 1.094 respectively) show that poor households benefit only slightly more from the program than non-poor households – which is partly due to the fact that the poverty threshold is set to include most of the population (67%). TD_1 and TD_2 are 0.0226 and 0.00185; higher than all other alternatives (except perfect targeting). The alternative PMT formula also performs slightly

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worse than the project PMT formula, suggesting that using a reduced regional specific formula would not improve targeting efficiency.

When considering the simulated impact of cash transfers on poverty, the differences between targeting methods is not as apparent. Community targeting, while not performing as well as other methods, still reduces poverty headcount by 13.5 percentage points. PMT targeting reduces poverty headcount by 19.1 percentage points (compared to 17.7 percentage points for random targeting). Poverty severity is reduced by 7.56 under PMT targeting, which is relatively close from perfect targeting poverty severity reduction of 9.18.[20] Universal targeting does not perform as well as PMT in terms of headcount reduction (16.9 percentage points), but performs similarly in terms of poverty severity reduction (7.17 for universal targeting). Differences between the PMT and the alternative PMT targeting methods are negligible.

When the threshold is fixed at the village level (see section 2.C), community targeting is relatively efficient, especially in terms of TD (0.209) and CGH (1.085), but inclusion errors (21.9%) and exclusion errors especially (41.3%) remain high (Table 6).[21] Community targeting again does not perform clearly better than random targeting, especially in terms of poverty reduction where random targeting has a greater simulated impact. PMT targeting continues to outperform community targeting (and random targeting) under all the metrics used. Inclusion and exclusion errors are still low (20.6% and 17.3%) and the TD is quite high (0.33). The alternative PMT formula again performs slightly worse than the base PMT. TD_1 is higher for PMT and PMT alternative compared to other targeting methods, but TD_2 is higher for universal targeting. Also, interestingly, universal targeting (with equal budget, i.e. reduced per capita

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[20] For comparison purposes, poverty incidence and poverty gap are presented in percentage points and poverty severity is multiplied by 100.
[21] Because the definition of poverty is different with global or village thresholds, results of Table 5 and Table 6 are not directly comparable.

transfers) performs better than PMT targeting in terms of poverty incidence reduction – but not for poverty gap and severity reduction, which are, arguably, more relevant.

Beyond the efficiency of CBT, it is useful to assess how hybrid targeting performs compared to the PMT in order to understand if CBT can be combined with PMT targeting to improve targeting performance. Hybrid targeted households are those with the lowest PMT scores among households selected by the community. So comparing hybrid to PMT targeting essentially means analyzing the effect of excluding some households with community targeting. Table 7 compares the hybrid targeting method used in the project (to select beneficiaries of the SSNPP) with PMT targeting, using the same indicators: exclusion errors, Targeting Differential (TD), CGH index (CGH_{35}) and simulated poverty reduction. Here, the per capita poverty threshold is adjusted to include the 35% poorest households globally (see section 2.C).

Hybrid and PMT targeting perform similarly for inclusion errors (51.1% and 51.6%) but hybrid exclusion errors are much higher (59.5%) than PMT targeting exclusion errors (44.7%).[22] This indicates that while using hybrid targeting may reduce PMT survey costs (if only households selected by the community are surveyed), exclusion errors are increased. However, both PMT and hybrid targeting clearly outperform random targeting. PMT targeting has a higher TD (0.142) and CGH index (1.277) than hybrid targeting, but its overall performance is not very impressive. In terms of TD_1 and TD_2, PMT also outperforms hybrid targeting, and both are considerably above random and universal targeting (whose TD_1 and TD_2 are negative). Poverty indices (FGT_0, FGT_1, FGT_2) reduction is also greater for PMT targeting alone compared to hybrid targeting. Interestingly, poverty severity (FGT_2) reduction is slightly higher for universal targeting (with equal budget than PMT and hybrid targeting). As before, results in terms of poverty reduction are still far from those obtained with perfect targeting. When adjusting the poverty and PMT thresholds at the village level (Table 8), PMT targeting still outperforms hybrid targeting under

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[22] Because the threshold is lower than in previous tables (lower level of coverage), error rates are higher.

all the metrics used, and PMT targeting TD (0.242) and CGH index (1.524) are relatively high. Universal targeting poverty incidence reduction (11.3 percentage point) is almost as high as with PMT targeting (11.9 percentage point), and PMT targeting only slightly outperforms universal targeting in terms of poverty gap and severity reduction. TD_1 and TD_2 are also higher for universal targeting than for PMT targeting. This better performance of universal targeting is explained by the high error rates of PMT and hybrid targeting when the target share of the population is lower (35%).

A gap between targeting efficiency in ex-ante simulations of beneficiary selection and in ex-post assessment is to be expected for several reasons including: i) the time elapse between the time of collection of the dataset used to generate the PMT (2007) and the PMT assessment (2013); and ii) the fact that Soulédé-Roua households are much poorer than those used for the design of the PMT formula. In previous nationwide studies with the survey from which the PMT was designed, inclusion and exclusion errors with the PMT formula were found between 20% and 25% (depending on the specification) in ex-ante simulations when targeting chronic poor households (52% of the targeted areas population) (Nguetse-Tegoum & Stoeffler, 2012). In Soulédé-Roua, PMT inclusion and exclusion errors are about 21% and 17% respectively when using the 67% selection threshold. However, inclusion and exclusion errors rise to about 40-50% when the lower 35% hybrid (project) threshold is used. This suggests that a large part of the difference between PMT performance in ex-ante and ex-post assessments may be due to the change of threshold, rather than performance decay in ex-post situations only. [23] Indeed, PMT targeting performance appears to decrease rapidly when the level of coverage falls, one of the drawbacks of PMT targeting noted by Kidd and Wylde (2011).

The single index measures above, are mostly based on binary indicators (poor/non-poor, excluded/included). A broader comparison of the distribution of per capita consumption of targeted and

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[23] Errors of inclusion and exclusion are 35% and 30% respectively, when using 52% PMT targeting and poverty levels to compare ex-post results with ex-ante simulations. As noted, this is about 10% point higher than in ex-ante simulations.

non-targeted households can be made with non-parametric kernel densities and related cumulative

distribution functions.[24] Overall, the log per capita consumption distribution for households chosen by

CBT is not significantly different from the distribution for households not chosen by CBT (Panel A, Figure

1) in a Kolmogorov-Smirnov test. However, comparison of the cumulative density functions (CdFs)

suggests that the community may be more efficient at including the poorest households but also

includes the wealthiest. By contrast for PMT targeting, a Kolmogorov-Smirnov test rejects the null

hypothesis of equality of distribution of log of per capita consumption for PMT and non-PMT selected

households. Moreover, the CdFs for households selected and non-selected by the PMT indicate that

selected households are clearly more likely to be poor over the entire per capita consumption

distribution (Panel B, Figure 1).

The same patterns are confirmed for hybrid (project) targeted and non-targeted households (Panel A,

Figure 2) and PMT targeted and non-targeted households (Panel B, Figure 2) with a 35% beneficiary

threshold. Kolmogorov-Smirnov tests reject the null hypothesis of equality of distributions in both cases.

Hybrid selected households are clearly poorer than non-beneficiaries, but because community targeting

has a greater propensity to include non-poor households, PMT targeting alone is better than hybrid

targeting at discriminating between poor and non-poor households.

Overall, the analysis of non-parametric densities confirms the results obtained for exclusion and

inclusion errors, TD, CGH index and poverty reduction simulations. However, they also suggest that

community targeting may be slightly more efficient in including the poorest households (on the left tail

of the distribution), and that poor CBT performance stems from greater inclusion of households on the

upper right tail of the distribution.

B. Determinants of errors and drivers of community targeting

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[24] Only cumulative distribution functions figures are shown. Associated probability density function kernel non-parametric estimates are available upon request.

The characteristics of households incorrectly included or excluded by the targeting methods are explored using the probit models specified in the previous section. Table 9 presents the determinants of exclusion errors when a poor household is (erroneously) not selected by CBT (first column) or PMT (second column) without controls for actual per capita consumption. The third and fourth columns of the table present CBT and PMT estimates that include controls for actual per capita consumption, and column five includes controls for PMT scores (for CBT only).[25] Erroneous exclusion in CBT increases with primary education (compared to none), number of cows, owning a bicycle and having no solid walls. This suggest that communities overvalues primary education (compared to its value in terms of per capita consumption) and underestimates the correlation between solid walls and poverty status. On the other hand, the number of adults in the household, no owning land, and being member of an association reduce the risk of exclusion. These results suggest that the communities value long-term determinants of wealth rather than short term consumption by considering human, social and physical capital (education, physical assets, land and livestock). Making decisions based on these very basic assets however, leads to errors in terms of identifying households with low per capita consumption. The fact that association members have a lower risk of being excluded suggests that the consumption status of active members of the community may be easier to observe – and that they are less likely to be socially excluded.[26] Also, CBT has a lower probability of excluding households which evaluate themselves as poor, suggesting that CBT decisions match local perception of poverty– but the probability of erroneous exclusion increase for households which declare themselves unable to meet their needs without falling into debt. Finally, per capita consumption (in column 3) also increases the risk of exclusion errors, suggesting that community targeting is more efficient among the poorest households (consistent with kernel densities). The positive and significant coefficient on PMT score in column (5) indicates that PMT

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[25] For PMT targeting, the PMT scores alone predict selection perfectly.
[26] Association membership does not appear to be indicative of elite capture, as association membership does not increase inclusion errors (see below).

and community targeting have a higher probability to diverge for households which have a higher probability of being selected by the PMT – suggesting some complementarities do exist between the two methods.

For PMT targeting, the probability of exclusion errors increases for Christians and Animists (which represent the large majority of the population), polygamists and widows. On the other hand, the probability of exclusion errors is lower for households with primary and secondary education relative to those without education, households with a wasting child or a handicapped member, female and old household heads, large households[27], and households with no assets, no solid walls or no solid roof. Several of these variables are included in the PMT formula, which explains why they decrease exclusion errors. Interestingly, CBT and PMT determinants never influence exclusion errors in the same direction, again suggesting a potential for complementarities across variables, even though in practice PMT targeting alone performs better than hybrid targeting in the SSNPP (because of high exclusion errors in CBT).

Probit results for determinants of inclusion errors are presented in Table 10. Primary education (relative to no education) also increases inclusion errors in the PMT in addition to reducing exclusion errors. This likely stems from the fact that the PMT formula, based on national statistics, considers primary education as an indicator of poverty, whereas in Soulédé-Roua primary education is already considered as an achievement. Similarly, household size, having no assets, no solid walls or no solid roof, also increases PMT errors of inclusion (while they decreased errors of exclusion). Conversely, being Christian or polygamist (which increased errors of exclusion) reduce errors of inclusion, thus decreasing the likelihood of being selected regardless of actual poverty status. However, other variables reduce

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[27] One of the reasons for larger exclusion errors in CBT than PMT targeting is that the community tends to select smaller households. Thus, when aggregated across individuals, CBT exclusion errors for larger households are even greater than exclusion errors of smaller households from the PMT. However, when aggregated across households rather than individuals, CBT errors are still larger than PMT errors.

inclusion errors without increasing exclusion errors, in particular those thought to be associated with poverty: having a wasting child in the household, not owning land, and needing to go into debt to make meet ends meet. Several variables are also associated with an increase in inclusion errors without decreasing exclusion errors– which is the worst possible scenario: the total value of assets, owning a bicycle, having no toilets, or having a high dietary diversity score. The PMT does not take into account credit taken by households, which also increases inclusion errors.

All these results indicate a potential for improvement of the PMT formula by including additional, finer information (on value of assets, obtaining credit) and by generating a formula from the region where it is applied to take into account local conditions associated with non-poverty (such as primary education, household size, owning a bicycle, etc.). However, targeting efficiency indicators show that such a formula, when generated from the national statistics (ECAM 3), does not improve targeting efficiency. This is likely to be due to the small sample size used to build regional PMT formulas. Further, some of the additional variables (e.g. value of assets) are difficult to measure accurately. This makes their inclusion in a PMT formula costly (in terms of data collection) and/or increases the risk of targeting inaccuracy (if they are not well measured) or strategic behavior in household responses.

For CBT, the probability of erroneous inclusion decreases with household size, the number of cows, access to borrowed land, and houses with solid walls. However, the probability of inclusion errors increases with female headed households, the number of adults, the age of the household head, and households with no land or no agricultural tools. Similar to PMT targeting, the value of physical assets increase community targeting inclusion errors. Finally, the community is too likely to include households with self-evaluated bad health[28], who were also less likely to be excluded, indicating that the community considers this variable as important regardless of consumption status. Thus "targeting errors" may be

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[28] Health status is collected in the baseline survey (2013), one year after the CBT (2012). Consequently, we cannot conclude that communities target households with short-term health issues, but rather households with chronic or recurrent health problems.

due to a different conception of poverty rather than a lack of information, targeting committees inefficiency and/or elite capture. To explore this hypothesis, the rest of this section analyzes the specific drivers of community targeting.

Table 11 presents the drivers of CBT choice and confirms the previous results (determinants of exclusion and inclusion). It shows the probability of being selected by the community without controls (column 1), as well as controlling for per capita consumption (column 2), for PMT score (column 3) and for both (column 4). The probability of community selection decreases with primary education, household size, number of cows and owning of a bicycle. Surprisingly, the probability of selection decreases with several other variables which are usually associated with poverty: having a wasting child in the household, no solid walls, and needing to go into debt to meet ends. On the other hand, the probability of selection increases some variables that are commonly associated with poverty: self-evaluated bad health status, having no land, no agricultural tools, self-evaluated poverty, age of the household head, and being a widow. Selection probability also increases for members of associations and with the value of physical assets. These results suggest that the community has a conception of poverty which somewhat differs from simply per capita consumption or even basic accounting of physical assets. Indeed, the community tends to focus on households with limited income-generating potential, such as older, isolated households with low human capital and lack of basic productive physical assets. For instance, being a widow or having a self-evaluated bad health status increases the average probability of being selected by 7%, while having no agricultural tools increases selection probability by 11%. Finally, the negative and significant coefficient on PMT score (an indicator of the probability of poverty) indicates a divergence between the two targeting methods. This finding is now further analyzed.

The multinomial logit model is used to identify variables associated with being selected by the PMT only (column 1), by the CBT only (column 2), or by neither (column 3), compared to the baseline category,

being selected by both PMT and CBT (Table 12).[29] Variables which increase the probability of being

selected only by the PMT are those included in the PMT formula such as household size, owning a

bicycle, having no solid walls. However, number of cows also increases the probability of being selected

by the PMT only. Variables increasing the probability of being selected by the community only are being

Christian or Animist (these variables are associated with PMT exclusion errors), being a widow,

borrowing land. Having secondary education, household size, having no solid walls, solid roof or toilets

decrease the probability of being selected by CBT only (compared to being selected by PMT and CBT).

Also, being a member of an association decreases the probability of being selected by PMT only or by

CBT only. Finally, self-evaluated bad health and not owning land decrease the probability of being in

each of the three categories, which suggest that households with these deprivations tend to be selected

by both CBT and PMT. Some deprivations are only taken into account by CBT, such as being a widow,

but in general, households with a given deprivation have a greater probability of being selected by both

targeting methods. These results suggest that CBT and PMT do not diverge radically but that CBT focuses

more on the socio-economic condition of households (e.g. being a widow, borrowing land) rather than

on household assets.

Overall, and consistent with findings from other countries (Alatas et al., 2012; Pop, 2014), the regression

results suggest that CBT does not focus on low per capita consumption and its correlates (house

material, etc.) and uses different criteria than PMT targeting. Specifically, CBT seem to exclude

households with obvious signs of physical wealth (cows, physical assets) and include more households

with low human capital (education and health) and limited resources (widows, households with no land

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[29] Several tests of Independence of Irrelevant Alternatives (IIA) were performed: Hausman tests, suest-based Hausman tests and Small-Hsiao tests, on the Table 12 specification as well as on alternative specifications (excluding the category "neither" or changing the base category). All tests fail to reject the null hypothesis (independence of other alternatives) except for the "neither" category in some tests – which is the category for which we don't interpret coefficients. Some Hausman tests could not be performed because of negative chi-square values, which is usually an indication that the IIA hypothesis holds (Long & Freese, 2006, pp. 244-245).

or no agricultural material, etc.). Therefore, we evaluate CBT selection under alternative definitions of poverty.

C. Alternative Assessments of CBT

First, CBT efficiency in selecting the most food insecure households is assessed. A Household Food Insecurity Access Scale (HFIAS) score is constructed following Coates, Swindale and Bilinsky (2007). As when poverty is defined as per capita consumption, the 67% households with the highest HFIAS scores are defined as poor (food insecure) (similarly to Scenario 1, see section 2.C) and errors of inclusion and exclusion for PMT and CBT are computed as before.

Second, CBT efficiency in selecting multidimensionally poor households is assessed. A multidimensional poverty (MDP) index is constructed following a counting approach, which counts and aggregates dimensions in which each household is deprived (Alkire & Foster, 2011; Stoeffler, Alwang, et al., 2015). The dimensions considered are health, education, nutrition and food security, living standards, physical assets, vulnerability and self-evaluated poverty status.[30] Again, the 67% of households with the highest MDP index are defined as poor and errors of inclusion and exclusion for CBT and PMT are computed.

Third, the efficiency of the CBT in selecting households which are predicted as poor according to an empirical measure of the community selection criteria is assessed. We do this in a fashion similar to that employed in the creation of the PMT formula from the ECAM 3 dataset. The sample is randomly split and the first part (2/3 of the sample) is used to predict community selection using a simple probit model. Using the same variables and the weights obtained from the model, community selection is then predicted for the second part (1/3 of the sample). Households with the highest predicted probability of being selected by CBT in each village are defined as "community poor" households so that 67% of them are considered as "community poor". The efficiency of the community in selecting households

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[30] More details on the construction of the MDP index are available upon request.

corresponding to its own criteria is assessed by computing errors of inclusion and exclusion in the usual manner. The simulation is run 300 times, and average errors of inclusion and exclusion are computed.

Results from these three assessments of CBT efficiency still show high levels of errors from CBT (Table 13). CBT errors of inclusion are moderate: 26.4% for food insecurity and 27.3% for MDP, which is lower than with PMT targeting (31.7% and 34.4% respectively). However, errors of exclusion are 38.1% for food insecurity and 35.6% for MDP, which are much higher than PMT errors and also random targeting. When considering "community poor" households (those predicted to be selecting by the community), errors are still as high: 22.6% of inclusion errors and 41.2% exclusion errors. These results strongly suggests that if communities employ different criteria to select households, these criteria are either non-apparent with the data at hand or produce very variable outcomes. The results cast doubt on the capacity of communities in Soulédé-Roua to select poor households in a clear and consistent manner, regardless of the poverty criteria employed.

5. Conclusion and policy recommendations

This article studies the efficiency of two targeting mechanisms (CBT and PMT) employed in a pilot unconditional cash transfer project in Northern Cameroon. Results are informative regarding the actual performance of targeting methods in projects implemented in extremely poor, rural, Sub-Saharan African environments. The findings are not very encouraging for CBT performance relative to PMT performance when per capita consumption is used to define poverty. Further, CBT consistently performs worse than PMT targeting when alternative indicators and program thresholds are used – and in many cases worse than random selection. Contrary to other studies like Alatas et al. (2012), in Soulédé-Roua transfers under CBT have a significantly lower simulated impact on poverty than transfers delivered by PMT targeting. Hybrid CBT and PMT targeting performs worse than PMT targeting alone. Thus CBT does not appear to directly complement PMT to improve targeting performance. Results also raise questions

about the efficiency of PMT targeting, as with the PMT exclusion and inclusion errors are above 40% and simulated impacts on poverty are not clearly higher than simulated impacts from universal transfers with an equal aggregate budget.

The analysis of the determinants of targeting errors suggests that the PMT formula is slightly disconnected from the local context of Soulédé-Roua, which is poorer than the nation as a whole from which the PMT formula is estimated. This implies potential gains from estimation of a local or regional formula. However, a PMT formula generated at the regional level does not perform better when tested. Poor performance of the regional PMT may stem from the need to collect original, regional, and recent data to design PMT formulas adapted to the local environment.

Despite the poor performance of hybrid targeting, the fact that variables associated with errors of inclusion and exclusion differ greatly in PMT and CBT suggest there may exist potential complementarities between PMT and community targeting that could be exploited to increase targeting efficiency. Many variables associated with community selection are arguably components of multidimensional poverty (low human and physical capital) and further analysis is needed on complementarities in CBT performance across different dimensions of poverty.

PMT and CBT targeting differences may also stem in part from communities having a different conception of poverty than simply being below a per capita consumption threshold. In Soulédé-Roua, CBT focuses on vulnerable households with limited income potential due to an observable lack of human or physical capital. However, some of the characteristics associated with a reduction of exclusion errors (such as being a member of an association) suggest that lack of information sometimes limits CBT efficiency. Targeting efficiency of CBT was also tested using different methods and definitions of poverty (food security, multidimensional poverty and community-based PMT). Results suggest that CBT produces very variable beneficiary selection outcomes on observationally similar households. This may

stem from difficulties in generating a consistent process for community selection both across and within villages.

The poor performance of CBT in terms of per capita consumption and the implementation gap noticed in the pilot project regarding community targeting selection rates per village both suggest a need to improve community targeting performance by providing guidance, clear objectives, and definitions of poverty that are consistent with the policy objective and local perception, as well as through enforcement of the rules of the program. As noted, targeting efficiency depends on well-designed methods as much as on good implementation (Coady et al., 2004). Possible means for improving the work of community targeting committees include household visits and household ranking (rather than only separating poor from non-poor), as well as respecting village selection rate targets. Further research should focus on developing indicators of targeting efficiency which are related the targeting criteria used by the community to select poor households. This would help disentangle poor targeting efficiency (due to capture elite, lack of information or any other reason) from differences in the definition of poor households. It is also worth noting that CBT has other benefits in terms of satisfaction and project efficiency which are expected from the involvement of the community that need to be weighted along with quantitative targeting performance during method selection.

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Table 1: Number of households selected by each method

	PMT	Non-PMT	Total
Community	720 (41.79%)	443 (25.71%)	1163 (67.5%)
Non-Community	443 (25.71%)	117 (6.79%)	560 (32.5%)
Total	1163 (67.5%)	560 (32.5%)	1723 (100%)

Note: Number of households without using sample weights. By construction, the same number of households are selected by the community and by the PMT, 1163 households or 67.5% of the households (see section 2.C).

Table 2: Descriptive Statistics

	Mean, All	Selected by community	Lower 67% PMT scores	Project Beneficiary (Hybrid targeting)
Per capita consumption expenditures (FCFA, yearly)	80742.0	80861.2	75698.3	71770.1
PMT score (project)	3257.7	2617.5	5346.2	6560.1
Selected by the community (as poor)	0.537	1	0.500	0.994
Beneficiary of the project (hybrid targeting)	0.341	0.630	0.430	1
Age of the household head	45.78	46.67	46.02	46.79
Household size	7.463	7.199	8.138	8.490
Woman household head	0.200	0.230	0.166	0.165
Polygamist	0.377	0.347	0.410	0.411
Household head is widow	0.0626	0.0840	0.0425	0.0434
Young children number (0-4)	1.580	1.452	1.687	1.644
Children number (5-14)	2.604	2.452	3.085	3.361
Household members between 15 and 59	2.875	2.896	3.073	3.325
Elderly number (>60)	0.338	0.352	0.330	0.335
Nobody went to school in household	0.0913	0.108	0.0533	0.0433
Primary education	0.596	0.573	0.619	0.589
Secondary 1 education	0.241	0.233	0.256	0.270
Secondary 2 education	0.0718	0.0855	0.0719	0.0976
Someone in the household can read	0.279	0.273	0.294	0.312
Christian	0.417	0.427	0.407	0.424
Muslim	0.0004	0.0007	0.0005	0.0011
Animist	0.413	0.392	0.416	0.377
No religion	0.168	0.177	0.174	0.193
Handicap	0.204	0.207	0.217	0.217
Health not good (self-evaluation)	0.198	0.236	0.189	0.220
Received shock (any type)	0.691	0.688	0.698	0.688
Received shock on individuals or house	0.195	0.214	0.185	0.203
Received shock on field	0.417	0.441	0.422	0.455
Received shock on animals	0.519	0.506	0.530	0.522
Estimated total loss due to shocks (any), total (thousand FCFA)	123.6	133.4	139.5	133.1
Household obtained credit	0.439	0.426	0.457	0.457
Household took credit for consumption	0.295	0.283	0.301	0.292
Household took credit for investment	0.0974	0.0964	0.112	0.119
Association member	0.117	0.135	0.118	0.149
Household has animals	0.775	0.761	0.788	0.784
Tropical Livestock Units (TLU)	0.734	0.638	0.805	0.736
Number of cows	0.296	0.209	0.329	0.234
Value of livestock sales	2.046	1.797	2.318	2.373
This household owns land	0.667	0.629	0.680	0.634
Total land surface	8845.8	9604.0	9290.0	11606.7
This household borrows land	0.509	0.507	0.510	0.534
Grows cotton	0.394	0.381	0.427	0.446
Grows rice	0.135	0.134	0.137	0.146
Household grows maize	0.496	0.491	0.520	0.527

Hired labor	0.101	0.0925	0.0930	0.0905
Household owns no agricultural tools	0.0514	0.0613	0.0486	0.0546
Household bought (paid) fertilizer	0.435	0.416	0.459	0.477
Value of agricultural sales	75.39	101.7	88.36	146.0
Has Micro-enterprise	0.255	0.224	0.257	0.235
Micro-enterprise profits (if has ME)	43.33	33.57	43.88	40.50
Micro-enterprise equipment value (FCFA)	17.49	22.45	14.23	7.250
Some assistance available (any type)	0.777	0.772	0.772	0.748
Types of assistance (#)	1.731	1.745	1.722	1.702
Value assets (FCFA)	46.89	52.52	50.56	73.39
Types of assets (#)	0.504	0.510	0.495	0.560
No assets	0.710	0.713	0.712	0.701
Household asset index	0.333	0.318	0.327	0.356
The household owns at least 1 bicycle	0.0649	0.0501	0.0725	0.0637
Low Household Hunger Score	0.433	0.418	0.428	0.415
Moderate Household Hunger Score	0.389	0.398	0.387	0.388
Sever hunger (HHS)	0.178	0.184	0.185	0.197
Household Food Insecurity Access Scale (score)	12.06	12.33	12.07	12.35
Household Dietary Diversity Score	6.333	6.256	6.369	6.353
No solid walls	0.873	0.848	0.887	0.868
No solid roof	0.911	0.919	0.917	0.922
No toilets	0.0742	0.0735	0.0682	0.0759
Wasting child in the household	0.0674	0.0528	0.0763	0.0565
Stunting child in the household	0.157	0.141	0.168	0.149
Self-evaluated very poor	0.468	0.518	0.456	0.504
Needs to go into debt	0.541	0.516	0.548	0.541
Observations	1723	1163	1163	598

Descriptive Statistics for households in Soulédé-Roua. For comparison purposes, per capita consumption threshold is adjusted to obtain 67% of the households as poor. PMT threshold is adjusted to obtain 67% of the households targeted, community targeting is the method used in the project (67% selected). Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

Table 3: Comparison Scenarios

	CBT and PMT (67%)	Hybrid targeting and PMT (35%)
Global Level	**Scenario 1**: CBT/PMT global level	**Scenario 2**: Hybrid/PMT global level
Village Level	**Scenario 3**: CBT/PMT village level	**Scenario 4**: Hybrid/PMT village level

Table 4: Targeting matrix

| | | Poverty Status | | Total |
		Poor	**Non-Poor**	
Beneficiary Status	**Beneficiary**	Correct Inclusion (**C1**)	Erroneous Inclusion (**E1**)	**B**
	Non-Beneficiary	Erroneous Exclusion (**E2**)	Correct Exclusion (**C2**)	**NB**
Total		**P**	**NP**	T

TABLE 5: Targeting performance, 67% global poverty threshold

	Community	PMT	PMT alternative	Perfect	Random	Universal
Inclusion errors	0.259	0.210	0.220	0	0.254	0.249
Exclusion errors	0.470	0.167	0.201	0	0.325	0
Targeting differential	-0.0297	0.163	0.116	1	-0.0190	0
TD_1	0.0102	0.0226	0.0207	0.0456	0.0113	0.0183
TD_2	0.00107	0.00185	0.00174	0.00318	0.000917	0.00175
CGH index	0.955	1.094	1.074	1.449	0.968	0.978
FGT_0 reduction (%)	-13.5	-19.1	-18.8	-26.3	-17.7	-16.9
FGT_1 reduction (%)	-8.83	-12.9	-12.5	-16	-10.8	-11.8
FGT_2 reduction (*100)	-5.31	-7.56	-7.36	-9.18	-6.08	-7.17

Targeting efficiency indicators for community and PMT targeting methods. For comparison purposes, per capita consumption threshold is adjusted to obtain 67% of the households as poor. PMT threshold is adjusted to obtain 67% of the households targeted, community targeting is the method used in the project (67% selected). FGT_0, FGT_1 and FGT_2 reductions are the result of simulations of transfers to household selected under each targeting mechanism. Universal targeting transfers are adjusted to match community and PMT targeting budget. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

TABLE 6: Targeting performance, 67% village poverty threshold

	Community	PMT	PMT alternative	Perfect	Random	Universal
Inclusion errors	0.219	0.206	0.212	0	0.243	0.303
Exclusion errors	0.413	0.173	0.203	0	0.313	0
Targeting differential	0.209	0.333	0.304	1	0.179	0
TD_1	0.0394	0.0564	0.0543	0.0991	0.0425	0.0499
TD_2	0.00532	0.00752	0.00725	0.0110	0.00594	0.00811
CGH index	1.085	1.201	1.179	1.506	1.091	1
FGT_0 reduction (%)	-10.8	-14.6	-13.8	-23.3	-12.5	-16.2
FGT_1 reduction (%)	-7.93	-11.1	-10.7	-13.6	-9.33	-10
FGT_2 reduction (*100)	-5.44	-7.33	-7.16	-8.4	-6.26	-6.4

Targeting efficiency indicators for community and PMT targeting methods. For comparison purposes, poverty (per capita consumption) and PMT thresholds are adjusted in each village to obtain as many households which are poor, targeted by the PMT and targeted by the community. FGT_0, FGT_1 and FGT_2 reductions are the result of simulations of transfers to household selected under each targeting mechanism. Universal targeting transfers are adjusted to match community and PMT targeting budget. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

TABLE 7: Targeting performance, 35% global poverty threshold

	Hybrid (project)	PMT	PMT alternative	Perfect	Random	Universal
Inclusion errors	0.511	0.516	0.517	0	0.606	0.589
Exclusion errors	0.595	0.447	0.486	0	0.654	0
Targeting differential	0.110	0.142	0.129	1	-0.0254	0
TD_1	0.00424	0.00567	0.00492	0.0328	-0.00261	-0.00543
TD_2	0.000272	0.000334	0.000248	0.00199	-0.000261	-0.000411
CGH index	1.273	1.277	1.245	2.778	0.910	0.964
FGT_0 reduction (%)	-10.6	-13.6	-12.6	-27.8	-9.54	-10.9
FGT_1 reduction (%)	-3.8	-4.8	-4.62	-9.08	-3.01	-4.54
FGT_2 reduction (*100)	-1.71	-2.1	-2.02	-3.88	-1.23	-2.2

Targeting efficiency indicators for Hybrid (project) and PMT targeting methods. For comparison purposes, per capita consumption threshold is adjusted to obtain 35% of the households as poor. PMT threshold is adjusted to obtain 35% of the households targeted, and Hybrid (project) targeting is the targeting method used in the project (35% selected). FGT_0, FGT_1 and FGT_2 reductions are the result of simulations of transfers to household selected under each targeting mechanism. Universal targeting transfers are adjusted to match project and PMT targeting budget. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

TABLE 8: Targeting performance, 35% village poverty threshold

	Hybrid (project)	PMT	PMT alternative	Perfect	Random	Universal
Inclusion errors	0.490	0.468	0.485	0	0.584	0.604
Exclusion errors	0.574	0.427	0.478	0	0.653	0
Targeting differential	0.157	0.242	0.200	1	0.0277	0
TD_1	0.0170	0.0245	0.0218	0.0560	0.0101	0.0311
TD_2	0.00139	0.00197	0.00175	0.00419	0.000864	0.00307
CGH index	1.415	1.524	1.467	2.938	1.062	1.000
FGT_0 reduction (%)	-9.88	-11.9	-11.8	-25.8	-8.43	-11.3
FGT_1 reduction (%)	-3.58	-4.67	-4.2	-8.11	-2.79	-4.02
FGT_2 reduction (*100)	-1.6	-2.14	-1.91	-3.46	-1.25	-1.91

Targeting efficiency indicators for Hybrid (project) and PMT targeting methods. For comparison purposes, poverty (per capita consumption) and PMT thresholds are adjusted in each village to obtain as many households which are poor, targeted by the PMT and targeted by the project (Hybrid). FGT_0, FGT_1 and FGT_2 reductions are the result of simulations of transfers to household selected under each targeting mechanism. Universal targeting transfers are adjusted to match project and PMT targeting budget. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

TABLE 9: Determinants of Exclusion Errors among Poor Households

	(1) Community exclusion error	(2) PMT exclusion error	(3) Community exclusion error	(4) PMT exclusion error	(5) Community exclusion error
Depend variable: being not selected by the targeting method. Sample: poor households.					
Household Characteristics					
Primary education	**0.241**[*]	**-0.613**^{***}	0.219	**-0.595**^{***}	0.200
	(1.65)	**(-4.98)**	(1.46)	**(-4.78)**	(1.32)
Secondary 1 education	0.194	**-0.547**^{***}	0.164	**-0.531**^{***}	0.148
	(0.93)	**(-3.12)**	(0.77)	**(-2.98)**	(0.69)
Secondary 2 education	-0.060	0.233	-0.090	0.250	-0.087
	(-0.23)	(0.92)	(-0.34)	(0.95)	(-0.33)
Wasting child in the household	0.181	**-0.540**[*]	0.184	**-0.533**[*]	0.206
	(1.28)	**(-1.77)**	(1.36)	**(-1.74)**	(1.46)
Christian	-0.061	**0.358**^{**}	-0.061	**0.369**^{**}	-0.053
	(-0.47)	**(2.33)**	(-0.49)	**(2.52)**	(-0.40)
Animist	0.040	**0.279**[*]	0.035	**0.285**[*]	0.038
	(0.29)	**(1.74)**	(0.26)	**(1.86)**	(0.27)
Handicap	0.074	**-0.237**[*]	0.099	**-0.260**[*]	0.071
	(0.95)	**(-1.91)**	(1.31)	**(-1.96)**	(0.92)
Health not good (self-evaluation)	-0.135	0.023	-0.113	0.008	-0.130
	(-1.10)	(0.24)	(-0.93)	(0.08)	(-1.08)
Received shock on field	-0.116	0.003	-0.137	0.016	-0.121
	(-0.83)	(0.04)	(-1.04)	(0.18)	(-0.88)
Woman household head	-0.005	**-0.154**[*]	-0.005	**-0.158**[*]	0.012
	(-0.04)	**(-1.70)**	(-0.04)	**(-1.72)**	(0.09)
Polygamist	0.047	**0.264**^{**}	0.043	**0.270**^{**}	0.056
	(0.66)	**(2.20)**	(0.61)	**(2.18)**	(0.78)
Household head is widow	-0.078	**0.404**[*]	-0.056	**0.401**[*]	-0.058
	(-0.48)	**(1.89)**	(-0.34)	**(1.88)**	(-0.35)
Household size	0.034	**-0.410**^{***}	**0.051**[*]	**-0.430**^{***}	-0.005
	(1.43)	**(-20.16)**	**(1.71)**	**(-14.43)**	(-0.13)
Household members between 15 and 59	**-0.112**^{***}	0.085	**-0.117**^{***}	0.092	**-0.104**^{**}
	(-2.58)	(1.44)	**(-2.58)**	(1.48)	**(-2.18)**
Age of the household head	-0.006	**-0.006**^{**}	-0.007	**-0.005**[*]	-0.007
	(-1.22)	**(-2.32)**	(-1.38)	**(-1.91)**	(-1.46)
Household obtained credit	0.020	-0.109	0.013	-0.102	0.010
	(0.28)	(-0.97)	(0.22)	(-0.93)	(0.14)
Association member	**-0.397**[*]	0.194	**-0.405**^{**}	0.188	**-0.382**[*]
	(-1.93)	(0.79)	**(-2.01)**	(0.79)	**(-1.92)**
Productive assets					
Number of cows	**0.236**[*]	0.006	**0.232**[*]	0.012	**0.251**[*]
	(1.77)	(0.07)	**(1.75)**	(0.14)	**(1.90)**
Value of livestock sales	0.006	-0.014	0.005	-0.014	0.005
	(1.40)	(-1.41)	(1.27)	(-1.36)	(1.31)
This household	0.168	0.132	0.145	0.156	0.177

borrows land	(1.06)	(1.23)	(0.93)	(1.41)	(1.10)
This household does not own land	**-0.277*****	-0.050	**-0.255*****	-0.075	**-0.287*****
	(-2.99)	(-0.38)	**(-2.80)**	(-0.56)	**(-3.18)**
Household bought (paid) fertilizer	0.223	-0.116	0.206	-0.102	0.212
	(1.33)	(-0.92)	(1.23)	(-0.82)	(1.29)
Household owns no agricultural tools	-0.228	0.156	-0.232	0.153	-0.215
	(-1.08)	(0.85)	(-1.11)	(0.84)	(-0.98)
Value of agricultural sales	-0.000	-0.003	-0.001	-0.003	-0.001
	(-0.74)	(-0.95)	(-0.82)	(-0.93)	(-0.85)
Has Micro-enterprise	0.177	0.088	0.175	0.092	0.172
	(1.54)	(0.76)	(1.56)	(0.81)	(1.49)
Standards of living					
Value assets (FCFA)	-0.001	-0.004	-0.001	-0.004	-0.001
	(-0.80)	(-1.56)	(-0.87)	(-1.57)	(-0.77)
No assets	0.044	**-0.361*****	0.049	**-0.369*****	0.026
	(0.23)	**(-2.82)**	(0.25)	**(-3.08)**	(0.13)
The household owns at least 1 bicycle	**0.469****	-0.251	**0.466****	-0.230	**0.473****
	(1.96)	(-0.64)	**(2.05)**	(-0.58)	**(2.10)**
No solid walls	**0.326***	**-0.272****	**0.320***	**-0.264****	**0.292***
	(1.82)	**(-2.08)**	**(1.81)**	**(-2.04)**	**(1.70)**
No solid roof	-0.183	**-0.380***	-0.154	**-0.407***	-0.215
	(-0.88)	**(-1.85)**	(-0.74)	**(-1.94)**	(-1.02)
No toilets	0.245	-0.014	0.261	-0.021	0.205
	(1.50)	(-0.08)	(1.58)	(-0.12)	(1.27)
Household Dietary Diversity Score	0.039	-0.000	0.013	0.022	0.042
	(1.36)	(-0.01)	(0.36)	(0.72)	(1.50)
Self-evaluated very poor	**-0.255****	0.073	**-0.249****	0.065	**-0.258****
	(-2.53)	(0.98)	**(-2.47)**	(0.86)	**(-2.54)**
Needs to go into debt	**0.172*****	0.067	**0.163*****	0.077	**0.177*****
	(3.06)	(0.92)	**(2.63)**	(1.05)	**(3.26)**
Log of per capita consumption			**0.284***	-0.241	
			(1.68)	(-1.52)	
PMT score (*0.001)					**0.026****
					(2.35)
Constant	-0.698	2.904*****	-3.711***	5.494*****	-0.385
	(-1.19)	(13.56)	(-1.88)	(3.18)	(-0.65)
Observations	1156	1156	1156	1156	1156
Log-Likelihood	-683.580	-435.781	-680.129	-434.154	-680.117

t statistics in parentheses
Probit model of determinants of being erroneously excluded from community and PMT targeting for poor households. For comparison purposes, the poverty line (per capita consumption threshold) is adjusted to obtain 67% of the households as poor. PMT threshold is adjusted to obtain 67% of the households targeted, community targeting is the method used in the project (67% selected). Standard Errors are clustered at the village level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 10: Determinants of Inclusion Errors

	(1) Community inclusion error	(2) PMT inclusion error	(3) Community inclusion error	(4) PMT inclusion error	(5) Community inclusion error
	Depend variable: being selected by the targeting method. Sample: non-poor households.				
Household Characteristics					
Primary education	-0.162	**0.410***	-0.168	**0.387***	-0.081
	(-1.06)	**(2.94)**	(-1.01)	**(2.88)**	(-0.52)
Secondary 1 education	-0.274	0.304	-0.279	0.291	-0.217
	(-1.50)	(1.45)	(-1.54)	(1.36)	(-1.14)
Secondary 2 education	-0.355	0.222	-0.360	0.224	-0.331
	(-1.51)	(0.60)	(-1.47)	(0.58)	(-1.37)
Wasting child in the household	-0.306	**-0.758****	-0.308	**-0.763****	-0.412
	(-1.05)	**(-2.37)**	(-1.05)	**(-2.46)**	(-1.55)
Christian	0.251	**-0.457***	0.252	**-0.450***	0.210
	(1.23)	**(-1.84)**	(1.26)	**(-1.80)**	(1.01)
Animist	0.131	-0.098	0.131	-0.107	0.134
	(0.65)	(-0.79)	(0.65)	(-0.83)	(0.67)
Handicap	0.022	0.107	0.022	0.101	0.068
	(0.15)	(0.98)	(0.15)	(0.93)	(0.45)
Health not good (self-evaluation)	**0.443***	-0.050	**0.446***	-0.040	**0.447***
	(3.68)	(-0.29)	**(3.58)**	(-0.24)	**(4.10)**
Received shock on field	0.145	-0.200	0.148	-0.178	0.148
	(1.45)	(-1.29)	(1.42)	(-1.17)	(1.41)
Woman household head	**0.265***	0.007	**0.264***	0.005	**0.254***
	(1.75)	(0.05)	**(1.75)**	(0.04)	**(1.69)**
Polygamist	-0.077	**-0.226***	-0.077	**-0.213***	-0.087
	(-0.53)	**(-1.77)**	(-0.52)	**(-1.65)**	(-0.57)
Household head is widow	0.295	-0.072	0.294	-0.098	0.289
	(1.61)	(-0.30)	(1.59)	(-0.41)	(1.64)
Household size	**-0.085****	**0.539***	**-0.088****	**0.493***	**-0.000**
	(-2.01)	**(8.53)**	**(-2.25)**	**(6.25)**	**(-0.00)**
Household members between 15 and 59	**0.185****	-0.015	**0.186****	0.002	**0.182****
	(2.32)	(-0.14)	**(2.35)**	(0.02)	**(2.33)**
Age of the household head	**0.010***	0.001	**0.010***	0.001	**0.011****
	(1.84)	(0.25)	**(1.85)**	(0.36)	**(2.10)**
Household obtained credit	0.020	**0.391***	0.017	**0.356***	0.063
	(0.10)	**(3.04)**	(0.08)	**(2.79)**	(0.29)
Association member	0.086	0.266	0.086	0.273	0.078
	(0.43)	(0.98)	(0.44)	(1.01)	(0.38)
Productive assets					
Number of cows	**-0.106***	-0.074	**-0.105***	-0.071	**-0.132***
	(-1.74)	(-0.70)	**(-1.73)**	(-0.67)	**(-1.79)**
Value of livestock sales	0.002	-0.009	0.002	-0.010	0.001
	(0.41)	(-0.86)	(0.41)	(-0.93)	(0.14)
This household borrows land	**-0.264***	-0.172	**-0.268***	-0.191	**-0.297***
	(-1.70)	(-0.73)	**(-1.75)**	(-0.81)	**(-1.88)**

This household does not own land	0.356***	-0.397**	0.356***	-0.411**	0.332***
	(3.53)	**(-2.10)**	**(3.51)**	**(-2.20)**	**(3.21)**
Household bought (paid) fertilizer	0.139	-0.015	0.140	-0.004	0.163
	(0.88)	(-0.10)	(0.88)	(-0.03)	(1.07)
Household owns no agricultural tools	0.521**	0.104	0.522**	0.108	0.542**
	(2.23)	(0.39)	**(2.23)**	(0.39)	**(2.27)**
Value of agricultural sales	0.000	0.001	0.000	0.001	0.000
	(0.26)	(0.39)	(0.28)	(0.57)	(0.17)
Has Micro-enterprise	-0.061	-0.348*	-0.060	-0.336*	-0.139
	(-0.34)	**(-1.78)**	(-0.33)	**(-1.69)**	(-0.81)
Standards of living					
Value assets (FCFA)	0.000**	0.000*	0.000*	0.000*	0.000**
	(1.99)	**(1.66)**	**(1.91)**	**(1.94)**	**(2.08)**
No assets	-0.074	0.392*	-0.078	0.363	-0.037
	(-0.30)	**(1.70)**	(-0.31)	(1.63)	(-0.15)
The household owns at least 1 bicycle	-0.322	0.645***	-0.321	0.696***	-0.274
	(-1.55)	**(2.60)**	(-1.55)	**(2.82)**	(-1.27)
No solid walls	-0.583**	0.507***	-0.580**	0.522***	-0.519*
	(-2.11)	**(3.70)**	**(-2.15)**	**(3.78)**	**(-1.84)**
No solid roof	0.132	1.233***	0.131	1.225***	0.284
	(0.91)	**(4.43)**	(0.91)	**(4.49)**	(1.58)
No toilets	0.052	0.298*	0.057	0.296*	0.178
	(0.38)	**(1.82)**	(0.43)	**(1.78)**	(1.35)
Household Dietary Diversity Score	-0.005	0.071**	-0.002	0.100**	0.004
	(-0.09)	**(2.14)**	(-0.04)	**(2.26)**	(0.08)
Self-evaluated very poor	-0.036	0.215	-0.037	0.216*	-0.014
	(-0.23)	(1.58)	(-0.24)	**(1.65)**	(-0.09)
Needs to go into debt	-0.105	-0.211*	-0.104	-0.187	-0.111
	(-0.57)	**(-1.65)**	(-0.56)	(-1.60)	(-0.58)
Log of per capita consumption			-0.047	-0.476	
			(-0.24)	(-1.44)	
PMT score (*0.001)					-0.055***
					(-4.77)
Constant	0.345	-4.486***	0.899	1.106	-0.488
	(0.57)	(-6.77)	(0.36)	(0.31)	(-0.81)
Observations	558	558	558	558	558
Log-Likelihood	-293.986	-237.471	-293.951	-235.583	-288.690

t statistics in parentheses

Probit model of determinants of being erroneously included by community and PMT targeting for non-poor households. For comparison purposes, the poverty line (per capita consumption threshold) is adjusted to obtain 67% of the households as poor. PMT threshold is adjusted to obtain 67% of the households targeted, community targeting is the method used in the project (67% selected). Standard Errors are clustered at the village level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 11: Determinants of Community Selection

	(1) No control	(2) Control: PMT scores	(3) Control: pc consumption	(4) Control: PMT scores and pc consumption
Dependent variable: being selected by the community. Sample: all households.				
Household Characteristics				
Primary education	**-0.211****	**-0.160***	**-0.221****	**-0.170***
	(-2.26)	**(-1.71)**	**(-2.27)**	**(-1.74)**
Secondary 1 education	-0.200	-0.154	-0.204	-0.158
	(-1.50)	(-1.16)	(-1.54)	(-1.19)
Secondary 2 education	-0.0883	-0.0615	-0.0902	-0.0637
	(-0.57)	(-0.39)	(-0.58)	(-0.41)
Wasting child in the household	**-0.206***	**-0.245****	**-0.210***	**-0.248****
	(-1.74)	**(-2.07)**	**(-1.80)**	**(-2.13)**
Christian	0.102	0.0885	0.105	0.0913
	(1.04)	(0.91)	(1.09)	(0.96)
Animist	0.000664	0.00186	0.00301	0.00418
	(0.01)	(0.02)	(0.03)	(0.04)
Handicap	-0.0426	-0.0330	-0.0495	-0.0399
	(-0.55)	(-0.41)	(-0.64)	(-0.50)
Health not good (self-evaluation)	**0.226****	**0.223****	**0.218****	**0.215****
	(2.16)	**(2.17)**	**(2.05)**	**(2.06)**
Received shock on field	0.131	0.136	0.139	0.144
	(1.18)	(1.22)	(1.28)	(1.31)
Woman household head	0.0759	0.0603	0.0728	0.0573
	(0.67)	(0.56)	(0.64)	(0.53)
Polygamist	-0.0761	-0.0861	-0.0724	-0.0825
	(-1.02)	(-1.18)	(-0.99)	(-1.15)
Household head is widow	0.220	0.201	**0.224***	0.205
	(1.64)	(1.47)	**(1.65)**	(1.49)
Household size	**-0.0446****	0.00363	**-0.0537****	-0.00526
	(-2.44)	(0.12)	**(-2.35)**	(-0.17)
Household members between 15 and 59	**0.126*****	**0.119*****	**0.128*****	**0.121*****
	(4.00)	**(3.60)**	**(3.93)**	**(3.56)**
Age of the household head	0.00670	**0.00802***	0.00709	**0.00841***
	(1.42)	**(1.65)**	(1.54)	**(1.76)**
Household obtained credit	-0.0135	0.00480	-0.0106	0.00773
	(-0.20)	(0.07)	(-0.16)	(0.12)
Association member	**0.280***	**0.265***	**0.279***	**0.264***
	(1.77)	**(1.73)**	**(1.77)**	**(1.74)**
Productive assets				
Number of cows	**-0.190****	**-0.207****	**-0.187****	**-0.204****
	(-2.19)	**(-2.35)**	**(-2.16)**	**(-2.33)**
Value of livestock sales	-0.00320	-0.00315	-0.00296	-0.00292
	(-1.11)	(-1.10)	(-1.06)	(-1.06)
This household borrows land	-0.206	-0.222	-0.200	-0.216
	(-1.46)	(-1.54)	(-1.43)	(-1.51)

This household does not own land	**0.290*****	**0.295*****	**0.281*****	**0.286*****
	(3.60)	**(3.84)**	**(3.35)**	**(3.58)**
Household bought (paid) fertilizer	-0.127	-0.115	-0.119	-0.108
	(-0.80)	(-0.74)	(-0.76)	(-0.70)
Household owns no agricultural tools	**0.328*****	**0.323*****	**0.337******	**0.332*****
	(1.91)	**(1.83)**	**(2.01)**	**(1.93)**
Value of agricultural sales	0.000485	0.000520	0.000555	0.000589
	(1.24)	(1.21)	(1.44)	(1.39)
Has Micro-enterprise	-0.149	-0.160	-0.148	-0.159
	(-1.36)	(-1.53)	(-1.36)	(-1.53)
Standards of living				
Value assets (FCFA)	0.0000486	**0.0000430*****	0.0000585	0.0000471
	(1.05)	**(1.95)**	(0.53)	(1.48)
No assets	-0.0843	-0.0574	-0.0954	-0.0683
	(-0.44)	(-0.31)	(-0.51)	(-0.37)
The household owns at least 1 bicycle	**-0.338******	**-0.329*****	**-0.332******	**-0.322******
	(-2.50)	**(-2.61)**	**(-2.45)**	**(-2.56)**
No solid walls	**-0.365******	**-0.325******	**-0.359******	**-0.319******
	(-2.16)	**(-2.03)**	**(-2.12)**	**(-1.99)**
No solid roof	0.146	0.203	0.139	0.195
	(1.24)	(1.60)	(1.17)	(1.55)
No toilets	-0.127	-0.0646	-0.122	-0.0602
	(-1.14)	(-0.59)	(-1.11)	(-0.55)
Household Dietary Diversity Score	-0.0159	-0.0167	-0.00463	-0.00569
	(-0.59)	(-0.62)	(-0.14)	(-0.17)
Self-evaluated very poor	**0.183*****	**0.191*****	**0.182*****	**0.190*****
	(1.87)	**(1.93)**	**(1.89)**	**(1.96)**
Needs to go into debt	**-0.150*****	**-0.155*****	**-0.147*****	**-0.152*****
	(-3.11)	**(-3.25)**	**(-2.99)**	**(-3.13)**
PMT score (*0.001)		**-0.0320*****		**-0.0319*****
		(-3.26)		**(-3.26)**
Log of per capita consumption			-0.0873	-0.0854
			(-0.76)	(-0.75)
Constant	0.572	0.145	1.522	1.076
	(1.11)	(0.28)	(1.12)	(0.81)
Observations	1714	1714	1714	1714
Log-Likelihood	-994.6	-987.1	-993.8	-986.4

t statistics in parentheses

Probit model of determinants of being selected by the community, whole sample. For comparison purposes, per capita consumption threshold is adjusted to obtain 67% of the households as poor.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 12: Multinomial Logit model of determinants of mismatch between community and PMT targeting, village threshold

Selection status category	Selected by the PMT, not the community	Selected by the community, not the PMT	Not selected by the PMT or the community
Dependent variable: selection status. Sample: all households.			
Household Characteristics			
Primary education	0.266	-0.282	0.0661
	(1.54)	(-1.46)	(0.31)
Secondary 1 education	0.248	-0.424	0.0553
	(1.05)	(-1.60)	(0.20)
Secondary 2 education	-0.0348	**-0.760[*]**	-0.135
	(-0.12)	**(-1.92)**	(-0.33)
Wasting child in the household	0.0185	0.271	**0.831^{**}**
	(0.07)	(0.84)	**(2.54)**
Christian	-0.189	**0.565[*]**	0.186
	(-1.10)	**(1.88)**	(0.87)
Animist	0.0690	**0.470^{**}**	0.263
	(0.36)	**(1.96)**	(1.02)
Handicap	0.205	-0.214	-0.261
	(1.11)	(-1.06)	(-1.34)
Health not good (self-evaluation)	**-0.316[*]**	**-0.431[*]**	**-0.801^{***}**
	(-1.66)	**(-1.82)**	**(-2.58)**
Received shock on field	-0.241	0.0160	-0.342
	(-1.34)	(0.07)	(-1.09)
Woman household head	-0.0688	-0.195	**-0.443^{**}**
	(-0.25)	(-0.78)	**(-2.20)**
Polygamist	0.139	-0.0537	0.119
	(0.79)	(-0.19)	(0.79)
Household head is widow	-0.413	**0.922^{***}**	0.389
	(-1.27)	**(3.39)**	(1.45)
Household size	**0.137^{***}**	**-0.590^{***}**	**-0.345^{***}**
	(3.93)	**(-9.02)**	**(-5.95)**
Household members between 15 and 59	**-0.271^{***}**	0.165	-0.0398
	(-3.47)	(1.56)	(-0.61)
Age of the household head	-0.0104	-0.00219	**-0.0163[*]**
	(-1.21)	(-0.31)	**(-1.67)**
Household obtained credit	0.0885	-0.0969	-0.117
	(0.47)	(-0.37)	(-0.60)
Association member	**-0.663^{**}**	**-0.509[*]**	-0.396
	(-1.98)	**(-1.88)**	(-0.94)
Productive assets			
Number of cows	**0.392^{**}**	0.114	0.282
	(2.31)	(0.84)	(1.29)
Value of livestock sales	0.00219	-0.0120	0.00812
	(0.47)	(-0.80)	(1.53)
This household borrows land	0.222	**0.789^{**}**	**0.980^{**}**

	(0.88)	**(2.48)**	**(2.45)**
This household does not own land	**-0.366***[*]	**-0.567***[**]	**-1.044***[***]
	(-1.94)	**(-2.05)**	**(-4.05)**
Household bought (paid) fertilizer	0.166	-0.129	0.0208
	(0.60)	(-0.39)	(0.05)
Household owns no agricultural tools	-0.401	-0.119	**-0.989***[*]
	(-1.36)	(-0.34)	**(-1.71)**
Value of agricultural sales	-0.000871	-0.000717	-0.00114
	(-1.25)	(-0.40)	(-0.61)
Has Micro-enterprise	0.149	0.128	**0.477***[**]
	(0.55)	(0.65)	**(2.33)**

	Standards of living		
Value assets (FCFA)	-0.000261	-0.0000563	**-0.0000625***[*]
	(-0.36)	(-1.54)	**(-1.77)**
No assets	0.245	0.0239	0.00328
	(1.01)	(0.10)	(0.01)
The household owns at least 1 bicycle	**0.899***[***]	0.305	0.0652
	(3.29)	(0.62)	(0.15)
No solid walls	**0.557***[**]	**-0.458***[**]	0.548
	(2.32)	**(-2.18)**	(1.14)
No solid roof	-0.193	**-0.715***[***]	**-0.683***[**]
	(-0.62)	**(-3.50)**	**(-2.00)**
No toilets	-0.0229	**-1.055***[**]	-0.342
	(-0.07)	**(-2.27)**	(-1.42)
Household Dietary Diversity Score	-0.0224	-0.0711	0.0156
	(-0.56)	(-1.42)	(0.20)
Self-evaluated very poor	-0.106	-0.221	**-0.514***[**]
	(-0.80)	(-0.91)	**(-1.98)**
Needs to go into debt	0.0802	0.0187	**0.497***[***]
	(1.00)	(0.11)	**(3.70)**
Constant	-1.179	3.382*[**]	1.663
	(-1.13)	(2.50)	(0.92)

# of households	321	321	239
Observations	1657		
Log-Likelihood	-1765.8		

t statistics in parentheses

Multinomial Logit model of determinants of being selected by the PMT but not the community, and vice versa. Baseline category: selected by PMT and community (881 households). For comparison purposes, the PMT thresholds are adjusted in each village to obtain as many households which are targeted by the community and by the PMT. Observations: 1657 households.

$* p < 0.10$, $** p < 0.05$, $*** p < 0.01$

TABLE 13: Targeting Errors with Alternative Poverty Definitions

	Community	PMT	PMT alternative	Random
Inclusion errors: Food Security	0.264	0.317	0.310	0.292
Exclusion errors: Food Security	0.381	0.205	0.220	0.281
Inclusion errors: Multidimensional Poverty	0.273	0.344	0.326	0.322
Exclusion errors: Multidimensional Poverty	0.356	0.195	0.197	0.275
Inclusion errors: Community criteria	0.226			
Exclusion errors: Community criteria	0.412			

Targeting efficiency indicators for community and PMT targeting methods with respect to Food Security (FS) and Multidimensional (MD) Poverty. For comparison purposes, Food Insecurity, Multidimensional Poverty and PMT thresholds are adjusted in each village to obtain as many households which are food insecure, multidimensional poor, targeted by the PMT and targeted by the community. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.
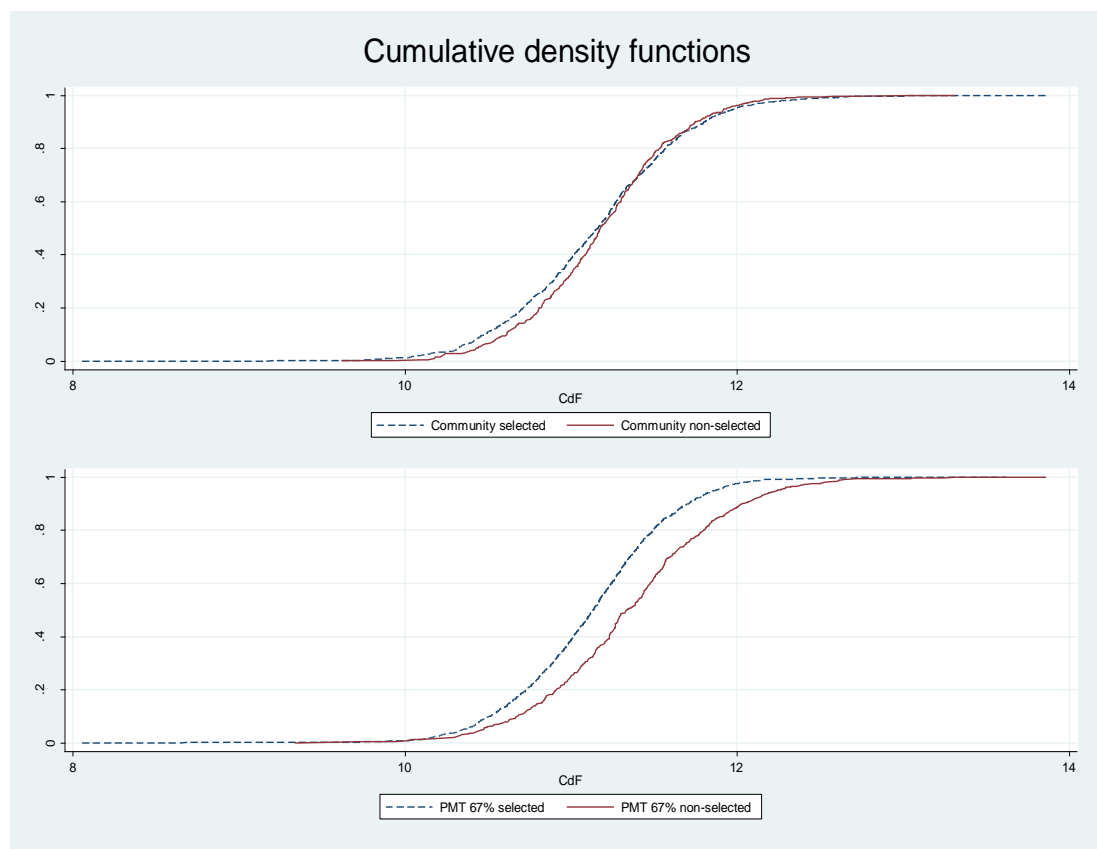
Figure 1: Per capita consumption by targeting group

Note: Cumulative density functions of log of per capita consumption aggregate by targeting group and selection. For comparison purposes, the PMT threshold is adjusted to obtain 67% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.
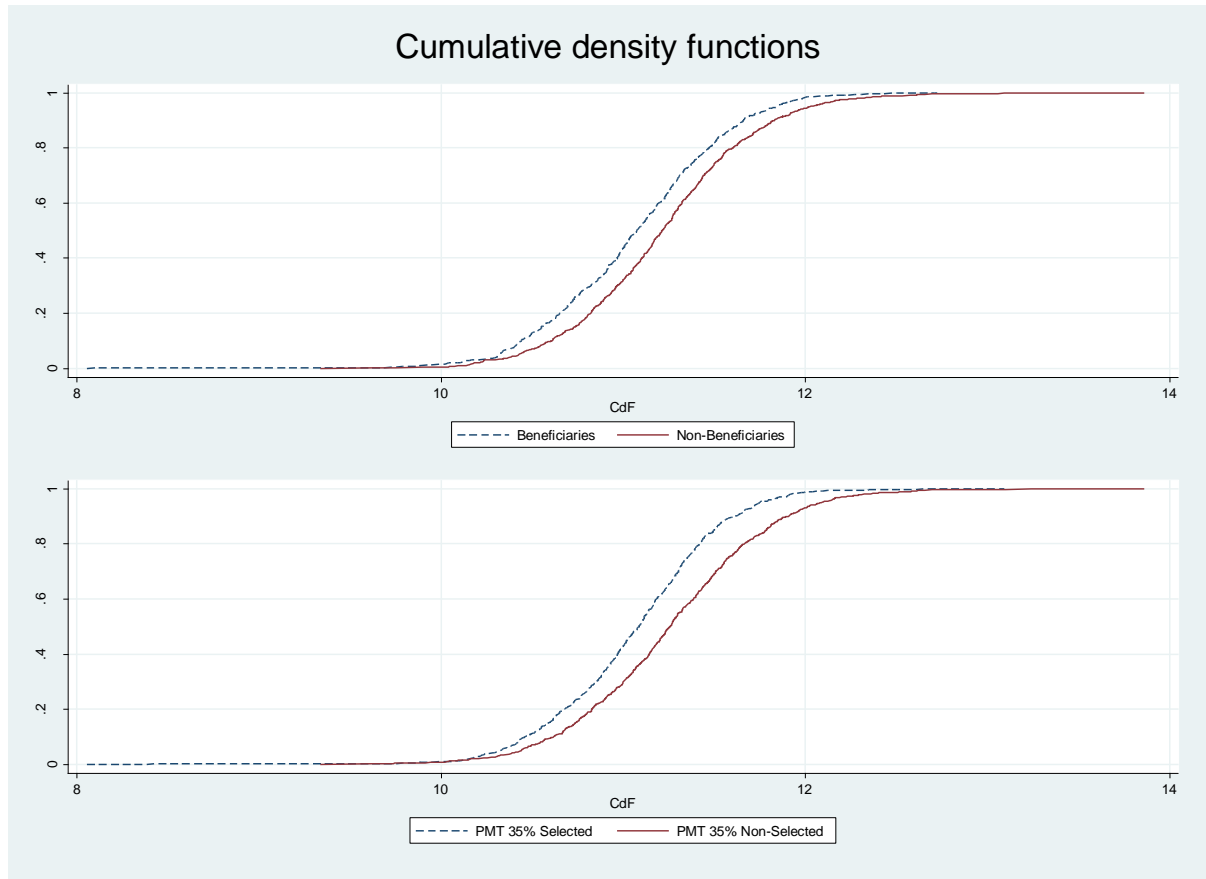
Figure 2: Per capita consumption by targeting group

Note: Cumulative density functions of log of per capita consumption aggregate by targeting group and selection. For comparison purposes, the PMT threshold is adjusted to obtain 35% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.