www.elsevier.com/locate/worlddev

World Development Vol. 83, pp. 244–263, 2016
0305-750X/© 2016 Published by Elsevier Ltd.

http://dx.doi.org/10.1016/j.worlddev.2016.01.012

Reaching the Poor: Cash Transfer Program Targeting in Cameroon

QUENTIN STOEFFLER [a], BRADFORD MILLS [b] and CARLO DEL NINNO [c,*]

[a] *University of California, Davis, CA, USA*
[b] *Virginia Tech, Blacksburg, VA, USA*
[c] *The World Bank, Washington DC, USA*

Summary. — Identifying and selecting poor households with efficient targeting methods is essential for effective poverty alleviation programs. 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. Several indicators and metrics to measure each method's performance in terms of inclusion of poor households and exclusion of non-poor households are employed. Results consistently show that CBT performs 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. However, CBT also shows more variability in the selection decision than PMT even when alternative poverty definitions are used as robustness tests. The PMT method used in the pilot slightly outperforms other targeting methods (hybrid, alternative PMT, and universal targeting with equal budget), but errors remain high when selecting 35% of the population for program participation. The results suggest caution is needed in employing CBT methods to select households with low per capita consumption in an environment where poverty levels are high and administrative capacities are limited. CBT performance may be improved through more uniform and consistent guidance on program selection criteria and process, including explicit criteria that enable CBT monitoring, as well as a better integration between PMT and CBT.

Key words — social assistance targeting, Proxy Means Testing (PMT), Community-Based Targeting (CBT), cash transfers, Sub-Saharan Africa, Cameroon

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 emphasizes 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 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

* We thank all the members of the Unité de Gestion Technique of the Social Safety Nets Pilot Project in Cameroon, and Pierre Nguetse, Victoria Monchuk, Jeff Alwang, George Norton and Wen You. Funding to support this work was provided by the World Bank. Nonetheless, the opinions expressed here are those of the authors and do not necessarily reflect those of the World Bank, its executive directors or the countries they represent. Final revision accepted: January 10, 2016.

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 and satisfaction (Robertson et al., 2014); (iii) increasing transparency of selection decisions among potential beneficiaries. [1] 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 et al., 2014; Pan & Christiaensen, 2012; Platteau, 2004). [2]

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 (Karlan & Thuysbaert, 2013). In particular, studies of specific programs have found 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 studies. Both PMT and CBT targeting are fully employed in an actual SSN project to 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. [3] 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 to 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. [4]

The main welfare indicator used in the analysis is per capita consumption. Clearly, the metric employed to identify the poor matters, and different metrics will result in the selection of different households (Glewwe & Van der Gaag, 1990; Laderchi, Saith, & Stewart, 2003). In the absence of a universally accepted definition of poverty, per capita consumption is considered to be the best metric given the program's objectives and means of intervention: providing cash payments to the chronic poor (as opposed for example to the provision of health benefits targeted toward ill households). Chronically poor households, arguably, do not have the *means* to realize achievement in most dimensions of well-being, for instance by buying medicine or school supplies. This is particularly true in areas with very high levels of deprivation such as Northern Cameroon. In these situations per capita consumption is a good indicator of chronic poverty and a pre-condition for meeting basic material needs and achieving well-being in other dimensions. While we recognized that poverty is multidimensional in nature (Alkire & Foster, 2011; Sen, 1999; Stoeffler, Alwang, Mills, & Taruvinga, in press), per capita consumption is widely considered as an important component of household well-being and used as a measure of living standards (Basu, 2013; Deaton & Zaidi, 2002). Other metrics are also employed to assess targeting performance (like a food consumption score and a multidimensional poverty index) as robustness tests (see Section 4(c)). [5]

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 compared to 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.

2. PROJECT DESCRIPTION AND DATA

(a) *Project and targeting*

High poverty rates and 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 chronic poor. The specific objective of the pilot was to build an integrated system of social safety nets to address chronic poverty, using cash transfer to the poorest as a central element. [6] 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 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, defined as households who, given their human, physical, and financial asset bases, are expected to remain poor in the future 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, delivered to women (when possible). This amount represents about 20% of average poor household consumption expenditures (Nguetse-Tegoum & Stoeffler, 2012). As , 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 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.[7] 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 complaints 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]

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.[9] 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 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 were 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 were 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. 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. 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. 1,723 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 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. Because its objective is to measure outcomes before these are affected by the intervention (cash transfers), the survey 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%) 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.

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)).

(c) *Comparing across targeting methods*

The per capita consumption aggregate (the main welfare indicator used in the analysis) 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). [12] 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 Section 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 (in the SSNPP, the PMT threshold was adjusted in ordered to obtain the desired 35% inclusion rate). [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 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; note that "local" universal targeting in our sample 15 villages is in reality geographic targeting, because the pilot project selected the poorest villages in one of the poorest areas of Cameroon. 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]

It would be useful to compare targeting costs, but unfortunately we do not have good information on these costs, as they are not easily disentangled from other project costs, especially during the pilot phase of the project. All cash transfer programs (targeted or universal) include some fixed costs associated with the building of a registry of beneficiaries. Even with universal targeting, a census is required of all households, especially those marginalized or less susceptible to apply for eligibility. Estimates suggest registration operations have costs equivalent to about 7% of the sum transferred in cash to beneficiaries. The PMT survey itself represent about 6% of the sum transferred, whereas CBT operations (travels, consultant fees, etc.) represent about 1% of the transfers. These numbers are based on survey and consultant contracts, but in other settings, PMT and CBT costs have been found to be relatively similar (Alatas et al., 2012). These budgetary issues are discussed further when comparing targeting results.

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). [18] 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

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

(*continued on next page*)

Table 2 (*continued*)

	Mean, All	Selected by community	Lower 67% PMT scores	Project beneficiary (hybrid targeting)
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 Souléde-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

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 $\mathrm{E}(IE_r) = \frac{NP}{T}$ and $E(EE_r) = \frac{NB}{T}$. For universal targeting, $IE_u = \frac{NP}{T}$ and $EE_u = 0$.

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 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.[19]

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 $TD_\propto$ which extends the simple TD by taking into account distance from the poverty threshold. For a given targeting mechanism j:

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

where $\propto$ 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 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:

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

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

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 methods 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 is 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) (Foster, Greer, & Thorbecke, 1984) poverty indices:

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

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 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:

$$E(ee_{ij} = 1|\mathbf{X}_i) = \Phi(\beta_j \mathbf{X}_i + \varepsilon_{ij}), i \in P \quad (2)$$

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 robustness tests 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).[20] 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:

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

where NP is the set of non-poor households.[21]

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:

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

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 indicate 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):

$$\Pr(t_i = j|\mathbf{X}_i) = f(\beta_j \mathbf{X}_i + \varepsilon_i) = \frac{\exp(\beta_j \mathbf{X}_i)}{\sum_{l=1}^{4} \exp(\beta_l \mathbf{X}_i)}, \quad i \in A \quad (5)$$

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.[22] 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 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

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.

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.[23] 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).[24] 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 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.[25] This result can be explained by the fact that in this scenario (village thresholds), the selection rates are fixed at village level, whereas in the previous scenario (global threshold) the selection rate adjusts to include more households in poorer villages. This likely reduces PMT performance and makes it more comparable to universal targeting.

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%). Because the threshold is lower than in previous tables (lower level of coverage), error rates are higher. The results indicate 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

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.

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 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%), and by the village threshold which constrains PMT targeting.

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.[26] 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 non-targeted households can be made with non-parametric kernel densities and related cumulative distribution functions (density functions are available upon request). 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 (Top panel, Figure 1) in a Kolmogorov–Smirnov test.

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.

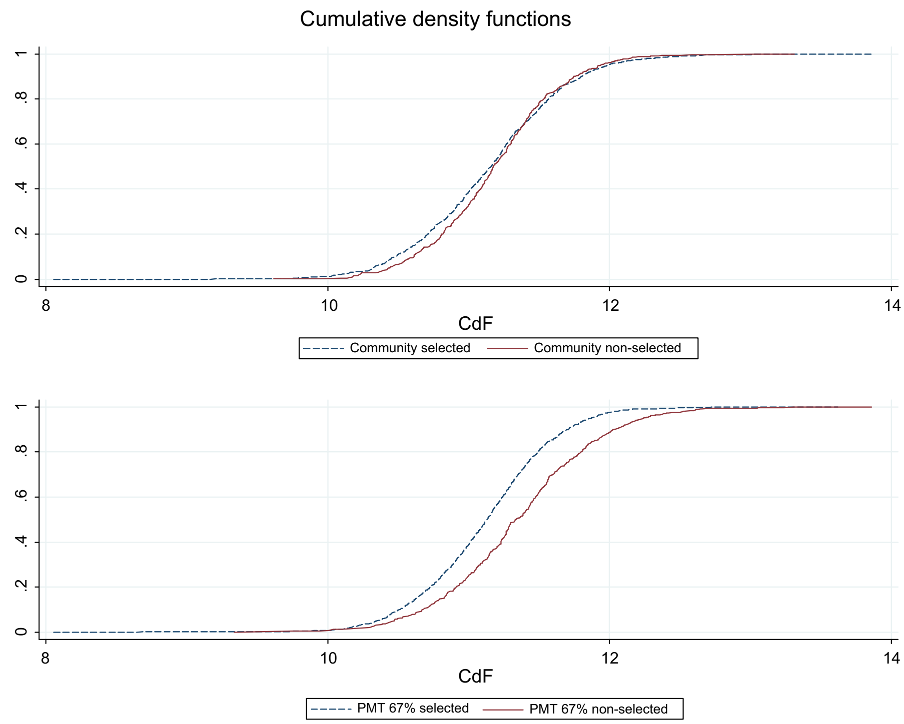

Figure 1. *Per capita consumption by targeting group. Note: Cumulative density functions of log of per capita consumption aggregate by targeting group and selection. For comparison purposes, the PMT threshold is adjusted to obtain 67% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.*

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 (Lower panel, Figure 1).

The same patterns are confirmed for hybrid (project) targeted and non-targeted households (Top panel, Figure 2) and PMT targeted and non-targeted households (Lower panel, 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*

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 (column 1) or PMT (column 2) without controls for actual per capita consumption. As robustness tests, estimations were conducted with alternative specifications controlling for actual per capita consumption (for CBT and PMT) and PMT scores (for CBT) and the results (available upon request) are largely unchanged.

Erroneous exclusion in CBT increases with primary education (compared to none), number of cows, owning a bicycle, and having no solid walls.[27] 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.[28] 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, in alternative specifications, per capita consumption also increases the risk of exclusion errors, suggesting that community targeting is more efficient among the poorest households (consistent with kernel densities). PMT score is positively and significantly

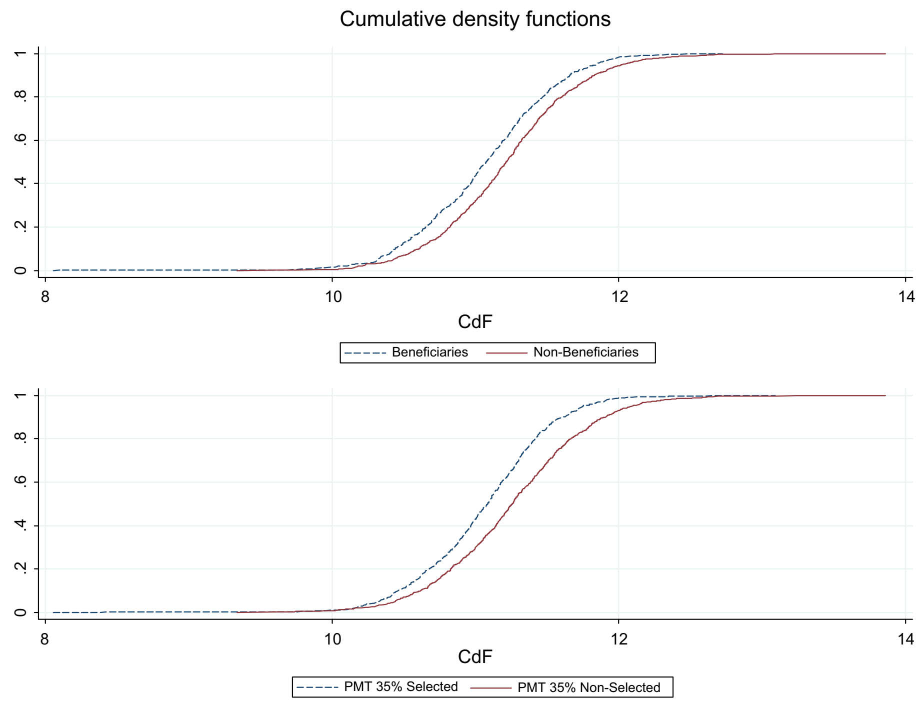

Figure 2. *Per capita consumption by targeting group. Note: Cumulative density functions of log of per capita consumption aggregate by targeting group and selection. For comparison purposes, the PMT threshold is adjusted to obtain 35% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.*

associated with CBT errors, indicating that PMT 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,[29] 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 (as well as why fewer variables are significantly associated with errors for CBT). 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 9 (columns 3 and 4). 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 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,[30] who were also less likely to be excluded, indicating that the community considers this variable as important regardless of con-

Table 9. *Determinants of exclusion errors among poor households*

	(1) Community exclusion error	(2) PMT exclusion error	(3) Community inclusion error	(4) PMT inclusion error
	Depend variable: being not selected by the targeting method. Sample: poor households		Depend variable: being selected by the targeting method. Sample: non-poor households	
Household characteristics				
Primary education	**0.241* (1.65)**	**−0.613*** (−4.98)**	−0.162 (−1.06)	**0.410*** (2.94)**
Secondary 1 education	0.194 (0.93)	**−0.547*** (−3.12)**	−0.274 (−1.50)	0.304 (1.45)
Secondary 2 education	−0.060 (−0.23)	0.233 (0.92)	−0.355 (−1.51)	0.222 (0.60)
Wasting child in the household	0.181 (1.28)	**−0.540* (−1.77)**	−0.306 (−1.05)	**−0.758** (−2.37)**
Christian	−0.061 (−0.47)	**0.358** (2.33)**	0.251 (1.23)	**−0.457* (−1.84)**
Animist	0.040 (0.29)	**0.279* (1.74)**	0.131 (0.65)	−0.098 (−0.79)
Handicap	0.074 (0.95)	**−0.237* (−1.91)**	0.022 (0.15)	0.107 (0.98)
Health not good (self-evaluation)	−0.135 (−1.10)	0.023 (0.24)	**0.443*** (3.68)**	−0.050 (−0.29)
Received shock on field	−0.116 (−0.83)	0.003 (0.04)	0.145 (1.45)	−0.200 (−1.29)
Woman household head	−0.005 (−0.04)	**−0.154* (−1.70)**	**0.265* (1.75)**	0.007 (0.05)
Polygamist	0.047 (0.66)	**0.264** (2.20)**	−0.077 (−0.53)	**−0.226* (−1.77)**
Household head is widow	−0.078 (−0.48)	**0.404* (1.89)**	0.295 (1.61)	−0.072 (−0.30)
Household size	0.034 (1.43)	**−0.410*** (−20.16)**	**−0.085** (−2.01)**	**0.539*** (8.53)**
Household members between 15 and 59	**−0.112*** (−2.58)**	0.085 (1.44)	**0.185** (2.32)**	−0.015 (−0.14)
Age of the household head	−0.006 (−1.22)	**−0.006** (−2.32)**	**0.010* (1.84)**	0.001 (0.25)
Household obtained credit	0.020 (0.28)	−0.109 (−0.97)	0.020 (0.10)	**0.391*** (3.04)**
Association member	**−0.397* (−1.93)**	0.194 (0.79)	0.086 (0.43)	0.266 (0.98)
Productive assets				
Number of cows	**0.236* (1.77)**	0.006 (0.07)	**−0.106* (−1.74)**	−0.074 (−0.70)
Value of livestock sales	0.006 (1.40)	−0.014(−1.41)	0.002 (0.41)	−0.009 (−0.86)
This household borrows land	0.168 (1.06)	0.132 (1.23)	**−0.264* (−1.70)**	−0.172 (−0.73)
This household does not own land	**−0.277*** (−2.99)**	−0.050 (−0.38)	**0.356*** (3.53)**	**−0.397** (−2.10)**
Household bought (paid) fertilizer	0.223 (1.33)	−0.116 (−0.92)	0.139 (0.88)	−0.015 (−0.10)
Household owns no agricultural tools	−0.228 (−1.08)	0.156 (0.85)	**0.521** (2.23)**	0.104 (0.39)
Value of agricultural sales	−0.000 (−0.74)	−0.003 (−0.95)	0.000 (0.26)	0.001 (0.39)
Has Micro-enterprise	0.177 (1.54)	0.088 (0.76)	−0.061 (−0.34)	**−0.348* (−1.78)**
Standards of living				
Value assets (FCFA)	−0.001 (−0.80)	−0.004 (−1.56)	**0.000** (1.99)**	**0.000* (1.66)**
No assets	0.044 (0.23)	**−0.361*** (−2.82)**	−0.074 (−0.30)	**0.392* (1.70)**
The household owns at least 1 bicycle	**0.469** (1.96)**	−0.251 (−0.64)	−0.322 (−1.55)	**0.645*** (2.60)**
No solid walls	**0.326* (1.82)**	**−0.272** (−2.08)**	**−0.583** (−2.11)**	**0.507*** (3.70)**
No solid roof	−0.183 (−0.88)	**−0.380* (−1.85)**	0.132 (0.91)	**1.233*** (4.43)**
No toilets	0.245 (1.50)	−0.014 (−0.08)	0.052 (0.38)	**0.298* (1.82)**
Household Dietary Diversity Score	0.039 (1.36)	−0.000 (−0.01)	−0.005 (−0.09)	**0.071** (2.14)**
Self-evaluated very poor	**−0.255** (−2.53)**	0.073 (0.98)	−0.036 (−0.23)	0.215 (1.58)
Needs to go into debt	**0.172*** (3.06)**	0.067 (0.92)	−0.105 (−0.57)	**−0.211* (−1.65)**
Constant	−0.698 (−1.19)	2.904*** (13.56)	0.345 (0.57)	−4.486*** (−6.77)
Observations	1156	1156	558	558
Log-likelihood	−683.580	−435.781	−293.986	−237.471

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. Bold highlights significant coefficients.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

sumption status. Thus "targeting errors" may be due to a different conception of poverty rather than 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 10 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

Table 10. *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)**

(*continued on next page*)

Table 10 (*continued*)

	(1) No control	(2) Control: PMT scores	(3) Control: pc consumption	(4) Control: PMT scores and pc consumption
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. Bold highlights significant coefficients.
[*] $p < 0.10$.
[**] $p < 0.05$.
[***] $p < 0.01$.

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.[31] 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 11).[32]

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, and 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, and 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 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

Table 11. *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*****(3.29)**	0.305	0.0652
		(0.62)	(0.15)
No solid walls	**0.557****	**−0.458****	0.548
	(2.32)	**(−2.18)**	(1.14)

(*continued on next page*)

Table 11 (*continued*)

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
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. Bold highlights significant coefficients.
$^{*}p < 0.10$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

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 2(c) 2()) 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 et al., 2015). The dimensions considered are health, education, nutrition and food security, living standards, physical assets, vulnerability, and self-evaluated poverty status (details available upon request). 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.

A third metric is used to try to estimate community perception of poverty and assess whether CBT is efficient in consistently selecting these households which are poor under these "community criteria". 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 variables and the weights obtained from the model, community selection is then predicted for the second part (1/3 of the sample). The 67% of households with the highest predicted probability of being selected by CBT in each village from Probit estimates are defined as "poor under community criteria". The idea is that if communities have a different definition of poverty but apply this definition consistently, there should be a strong correspondence between households predicted as "poor under community criteria" (based on criteria elicited in 2/3 of the sample) and households actually selected by CBT. The efficiency of the community in selecting households corresponding to its own criteria is then 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 12). CBT errors

Table 12. *Targeting errors with alternative poverty definitions*

	Community	PMT	Random
Inclusion errors: food security	0.264	0.317	0.292
Exclusion errors: food security	0.381	0.205	0.281
Inclusion errors: multidimensional poverty	0.273	0.344	0.322
Exclusion errors: multidimensional poverty	0.356	0.195	0.275
Inclusion errors: community criteria	0.226		
Exclusion errors: community criteria	0.412		
Inclusion errors: per capita consumption (Table 5 results)	0.259	0.210	0.254
Exclusion errors: per capita consumption (Table 5 results)	0.470	0.167	0.325

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.

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 "poor under community criteria" 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.

After considering targeting costs, universal targeting—which is in fact geographic targeting in the poorest areas of Cameroon—seems to be an attractive alternative to PMT and CBT targeting in Soulédé-Roua. However, political support for universal targeting has been limited and significant budgetary issues remain with scaling up to less poor regions. Besides, PMT targeting costs appear to be small compared to the transfer amount (about 6%), and CBT costs even smaller (about 1%). Consequently, targeting method choice should focus heavily on targeting performance, program objectives, and community satisfaction rather than costs. Whether universal-geographic targeting performs better or worse than PMT and/or CBT in a program at scale (in several regions of the country), when tracking all targeting costs properly, is an important area for further research.

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 country 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.

While CBT performance is clearly very context-specific, findings from Northern Cameroon are relatively consistent with the situations described in different contexts (Alatas et al., 2012; Pop, 2014; Robertson et al., 2014). The poor performance of CBT in terms of per capita consumption, the difficulty in assessing and monitoring CBT using other metrics, and the implementation gap noticed in the Cameroon pilot project regarding community-targeting selection rates per village all suggest caution in using CBT in situations where there exists limited administrative capacity. CBT may in some cases be a preferred targeting methods because of its other advantages, including community involvement and its potential to decrease costs. However, there is 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. The potential to integrate PMT and CBT in implementation also exists, rather than running the two exercises in parallel. 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. Finally, CBT has other benefits in terms of community satisfaction and project efficiency that arise from the involvement of the community that need to be weighted along with quantitative targeting performance during method selection.

NOTES

1. 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.

2. 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).

3. 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.

4. Budgetary considerations are also important when comparing policy options. We do not have precise figures of targeting costs, but discuss the issue while noting that targeting costs are small compared to the value of the program transfers.

5. A challenge in assessing the performance of both CBT and PMT is to employ an objective indicator that differs from the targeting criteria; otherwise one will conclude tautologically that targeting is efficient. In particular, variables used to construct the multidimensional poverty index and the PMT often overlap. The goal of this article is not to argue for a "best" targeting method, but rather to evaluate the performance of different methods under specific objective criteria in order to guide targeting processes and policy.

6. The SSNPP is currently being scaled up in the five poorest regions of Cameroon, to deliver cash transfers to 40,000 households.

7. These criteria were suggested to communities for household selection. Communities were not asked directly to select households with low per capita consumption, as this concept is not straightforward to apply. Rather, suggested criteria are multidimensional proxies related to per capita consumption. Records of the specific criteria employed in community in each village are not available.

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 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 specific variables used in the PMT formula are: household head characteristics (gender, age, instruction level, religion, employment sector); household size and composition, type and status of housing, electricity source, cooking fuel, toilets type, material of walls, roof and floor of the house, and ownership of radio, television, motorcycle or bicycle, exploited or non-exploited agricultural land, and secondary housing. Variables were chosen because they are easily verifiable, intuitively associated with poverty, and were found to contribute to lower ex-ante errors of exclusion and inclusion. As noted, the objective of the formula is to select the chronic poor. Simple PMT methods are not efficient at picking up fluctuations in well-being due to exposure to shocks, and thus selecting transitory poor.

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: $\text{TLU} = 0.7 * \text{cows} + 0.01 * \text{chicken} + 0.1 * (\text{sheeps} + \text{goats} + \text{rabits} + \text{dogs} + \text{other poultry}) + 0.2 * \text{pigs} + 0.4 * \text{equines}$.

12. Consumption data collection is challenging, however measurement errors would in theory increase inclusion and exclusion error rates found compared to actual error rates– and so do short-term fluctuations in consumption. Consequently, our results are conservative regarding targeting performance. Note that an advantage of both PMT and CBT is that they do not rely directly on measurement of actual consumption.

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.

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. In practice, cash transfer projects have used either global or village thresholds for PMT targeting in Sub-Saharan Africa (McBride., 2014).

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

18. While targeting errors are often expressed for per capita consumption measures, the issue of leakage and undercoverage generalizes to other types of targeting, e.g. when targeting orphans leakage means that non-orphans receive benefits while undercoverage means that some orphans are not reached.

19. 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}.

20. The regression is conducted among the poor households, which means that in practice the dependent variable ("exclusion error") is "being not selected". This reduces endogeneity concerns associated with inclusion of independent variables like per-capita consumption and PMT score that are linked to program eligibility.

21. 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).

22. The difference between inclusion and exclusion errors (even for random targeting) is due to the fact that household size weights are applied to obtain individual-level figures.

23. For comparison purposes, poverty incidence and poverty gap are presented in percentage points and poverty severity is multiplied by 100.

24. Because the definition of poverty is different with global or village thresholds, results of Tables 5 and 6 are not directly comparable.

25. Indeed PMT is more efficient in selecting the poorest of the poor, but exclusion errors are mostly found close to the poverty line. Universal targeting does not generate any exclusion errors, and thus performs better in terms of impact on poverty incidence, but the associated lower level of transfers decreases universal transfer's impact on poverty gap and severity.

26. 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.

27. It should be noted that intra-household allocation issues may cause some households to have higher levels of assets and low per capita consumption.

28. Association membership does not appear to be indicative of elite capture, as association membership does not increase inclusion errors (see below). Information is not available on participation in specific associations, but associations are mostly farmer organizations, religious organizations, and saving/credit associations.

29. 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.

30. 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. It is also worth noting that self-evaluated ill status is difficult to measure accurately.

31. Communities also seem to perceive children as assets, whereas the PMT selects larger households because household size correlates with low per capita consumption. Similarly, CBT appears less likely to choose households which went into debt because access to credit may indicate that households have good prospects, while CBT over-includes widows which indicates bad prospects.

32. Several tests of Independence of Irrelevant Alternatives (IIA) were performed: Hausman tests, suest-based Hausman tests and Small-Hsiao tests, on the Table 11 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).

REFERENCES

Adato, M., & Roopnaraine, T. (2004). *A social analysis of the Red de Protección Social (RPS) in Nicaragua* IFPRI report. Washington, DC: International Food Policy Research Institute (IFPRI).

Ahmed, A. U., & Bouis, H. E. (2002). Weighing what's practical: Proxy means tests for targeting food subsidies in Egypt. *Food Policy, 27*(5–6), 519–540.

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., & Tobias, J. (2012). Targeting the poor: Evidence from a field experiment in Indonesia. *The American Economic Review, 102*(4), 1206–1240.

Alderman, H. (2002). Do local officials know something we don't? Decentralization of targeted transfers in Albania. *Journal of Public Economics, 83*(3), 375–404.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics, 95*(7), 476–487.

Basu, K. (2013). *Shared prosperity and the mitigation of poverty: In practice and in precept*. World Bank, Policy research working paper No. 6700.

Besley, T., & Kanbur, S. M. R. (1990). *The principles of targeting*. World Bank, Policy, research, and external affairs working paper 385.

Cameron, L., & Shah, M. (2014). Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia. *Economic Development and Cultural Change, 62*(2), 381–415.

Coady, D., Grosh, M., & Hoddinott, J. (2004). Targeting outcomes redux. *The World Bank Research Observer, 19*(1), 61–85.

Coates, J., Swindale, A., & Bilinsky, P. (2007). *Household Food Insecurity Access Scale (HFIAS) for measurement of food access: indicator guide*. Washington, DC: Food and Nutrition Technical Assistance Project, Academy for Educational Development.

Conning, J., & Kevane, M. (2002). Community-based targeting mechanisms for social safety nets: A critical review. *World Development, 30*(3), 375–394.

Cornia, G. A., & Stewart, F. (1993). Two errors of targeting. *Journal of International Development, 5*(5), 459–496.

Deaton, A., & Zaidi, S. (2002). *Guidelines for constructing consumption aggregates for welfare analysis* (Vol. 135). World Bank Publications.

Del Ninno, C., & Mills, B. (2014). *Effective targeting mechanisms for the poor and vulnerable in Africa*. Washington DC: World Bank.

Ellis, F. (2012). 'We Are All Poor Here': Economic difference, social divisiveness and targeting cash transfers in Sub-Saharan Africa. *Journal of Development Studies, 48*(2), 201–214.

Ferguson, J. (2013). Declarations of dependence: Labour, personhood, and welfare in southern Africa. *Journal of the Royal Anthropological Institute, 19*(2), 223–242.

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica: Journal of the econometric society*, 761–766.

Galasso, E., & Ravallion, M. (2005). Decentralized targeting of an antipoverty program. *Journal of Public Economics, 89*(4), 705–727.

Garcia, M., & Moore, C. M. (2012). *The cash dividend: The rise of cash transfer programs in Sub-Saharan Africa*. Washington, DC: The World Bank.

Glewwe, P., & Van der Gaag, J. (1990). Identifying the poor in developing countries: Do different definitions matter?. *World Development, 18*(6), 803–814.

Grosh, M., & Baker, J. L. (1995). *Proxy means tests for targeting social programs: Simulations and speculation*. Washington, DC: World Bank.

Grosh, M., Del Ninno, C., Tesliuc, E. D., & Ouerghi, A. (2008). *For protection and promotion: The design and implementation of effective safety nets*. World Bank.

Handa, S., Huang, C., Hypher, N., Teixeira, C., Soares, F. V., & Davis, B. (2012). Targeting effectiveness of social cash transfer programmes in three African countries. *Journal of development effectiveness, 4*(1), 78–108.

Karlan, D., & Thuysbaert, B. (2013). *Targeting ultra-poor households in Honduras and Peru (No. 19646)*. National Bureau of Economic Research.

Kidd, S., & Wylde, E. (2011). *Targeting the poorest: An assessment of the proxy means test methodology* AusAID research paper. Canberra, Australia: Australian Agency for International Development.

Laderchi, C. R., Saith, R., & Stewart, F. (2003). Does it matter that we do not agree on the definition of poverty? A comparison of four approaches. *Oxford Development Studies, 31*(3), 243–274.

Leite, P., Stoeffler, Q., & Kryeziu, A. (2015). Targeting effectiveness of social safety net programs in Senegal. In C. D. Ninno, & B. Mills (Eds.), *Effective targeting mechanisms for the poor and vulnerable in Africa*. Washington, DC: World Bank.

Long, J. S., & Freese, J. (2006). *Regression models for categorical dependent variables using Stata*. Stata press.

Maluccio, J. A. (2009). Household targeting in practice: the Nicaraguan Red de Protección Social. *Journal of International Development, 21*(1), 1–23.

Mansuri, G., & Rao, V. (2004). Community-based and-driven development: A critical review. *The World Bank Research Observer, 19*(1), 1–39.

McBride (2014). Evaluation of targeting methods and impact of the cash transfer pilot in Niger. In C. Del Ninno, & B. Mills (Eds.), *Effective targeting mechanisms for the poor and vulnerable in Africa*. Washington, DC: World Bank.

Mkandawire, T. (2005). *Targeting and universalism in poverty reduction*. United Nations Research Institute for Social Development.

Monchuk, V. (2013). *Reducing Poverty and Investing in People: The New Role of Safety Nets in Africa*. World Bank Publications.

Narayan, A., & Yoshida, N. (2005). *Proxy means tests for targeting welfare benefits in Sri Lanka*. Washington, DC: World Bank, <http://siteresources. worldbank. org/EXTSAREGTOPPOVRED/Resources/49344 0-1102216396155/572861-1102221461685/Proxy+ Means+ Test + for+ Targeting+ Welfare+ Benefits. pdf> Accessed 05.02.09.

Nguetse-Tegoum, P., & Stoeffler, Q. (2012). *Programme de transferts monétaires sociaux: le ciblage des pauvres chroniques*. World Bank.

Niehaus, P., & Atanassova, A. (2013). Targeting with agents. *American Economic Journal: Economic Policy, 5*(1), 206–238.

Olivier de Sardan, J. P. O., Hamani, O., Issaley, N., Issa, Y., Adamou, H., & Oumarou, I. (2014). Les transferts monétaires au Niger: le grand malentendu. *Revue Tiers Monde, 2*(2), 107–130.

Pan, L., & Christiaensen, L. (2012). Who is vouching for the input voucher? Decentralized targeting and elite capture in Tanzania. *World Development, 40*(8), 1619–1633.

Platteau, J. P. (2004). Monitoring elite capture in community-driven development. *Development and change, 35*(2), 223–246.

Pop, L. (2014). Options for targeting of safety nets in Ghana. In C. D. Ninno, & B. Mills (Eds.), *Effective targeting mechanisms for the poor and vulnerable in Africa*. Washington, DC: World Bank.

Ravallion, M. (2009). How relevant is targeting to the success of an antipoverty program?. *The World Bank Research Observer, 24*(2), 205–231.

Robertson, L., Mushati, P., Skovdal, M., Eaton, J. W., Makoni, J. C., Crea, T., *et al.* (2014). Involving communities in the targeting of cash transfer programs for vulnerable children: Opportunities and challenges. *World Development, 54*, 325–337.

Sabates-Wheeler, R., Hurrell, A., & Devereux, S. (2014). Targeting social transfer programmes: Comparing design and implementation errors across alternative mechanisms. WIDER working paper.

Schüring, E. (2014). Preferences for community-based targeting-field experimental evidence from Zambia. *World Development, 54*, 360–373.

Sen, A. (1995). The political economy of targeting. In D. Van de Walle, & K. Nead (Eds.), *Public spending and the poor*. World Bank: Washington, D.C.

Sen, A. (1999). *Development as freedom*. Oxford University Press.

Sharif, I. (2009). *Building a targeting system for Bangladesh based on proxy means testing*. World Bank, Human Development Network.

Slater, R., & Farrington, J. (2009). *Targeting of social transfers: A review for DFID*. London: ODI.

Stoeffler, Q., Alwang, J., Mills, B., & Taruvinga, N. (in press). Multidimensional poverty in crisis: Lessons from Zimbabwe. *Journal of Development Studies*. http://www.tandfonline.com/doi/abs/10.1080/00220388.2015.1087511.

Stoeffler, Q., & Mills, B. (2014). *Households' investments in durable and productive assets in Niger: quasi-experimental evidences from a cash transfer project 2014 annual meeting, July 27–29*. Minneapolis, Minnesota: Agricultural and Applied Economics Association.

Stoeffler, Q., Nguetse-Tegoum, P., & Mills, B. (2015). Generating a system for targeting unconditional cash transfers in Cameroun. In C. D. Ninno, & B. Mills (Eds.), *Effective targeting mechanisms for the poor and vulnerable in Africa*. Washington, DC: World Bank.

Van de Walle, D., & Nead, K. (1995). *Public spending and the poor*. Baltimore: Johns Hopkins University Press.

World Bank. (2011a). *Cameroon: Social safety nets* (pp. 114).

World Bank. (2011b). *Social safety net programs in Cameroon: A feasibility study* (pp. 112).