Three Essays on Poverty in Sub-Saharan Africa: Multidimensional Poverty Change in Zimbabwe; Long-Term Impact of Cash Transfers in Niger; and Targeting Efficiency of Social Protection Programs in Cameroon

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Abstract

This dissertation focuses on identifying the poor in Sub-Saharan Africa (SSA) and the potential of social assistance programs to address their condition. Each essay is related to one particular key step of the poverty alleviation agenda: poverty definition and measurement in Zimbabwe; targeting poor households in Cameroon; and impact evaluation of anti-poverty interventions in Niger.

The first essay explores changes in poverty across multiple dimensions in a period of dramatic economic crisis and recovery in Zimbabwe. The essay analyzes changes in household well-being between 2001, 2007 and 2011/12, using an Alkire-Foster multidimensional poverty index. Results indicate a large increase in multidimensional poverty across between 2001 and 2007, followed by a (smaller) decrease in poverty between 2007 and 2011/12 (recovery period after the hyperinflation peak in 2008). However, decomposition of the index shows significantly different trends in poverty dimensions over time, as for instance health related dimensions continued to deteriorate after 2007.

The second essay contributes to the policy debate on targeting by studying the ex-post efficiency of two targeting mechanisms employed in a cash transfer project in rural Cameroon: Proxy Means Testing (PMT) and community targeting. Results show a poor performance of community targeting in selecting households with low per capita consumption, compared to PMT targeting– whose errors remain high nonetheless. Communities tend to select small, isolated households with low physical and human capital, regardless of their actual consumption level, but produce variable outcomes. Overall results suggest that a higher coverage contributes to reducing targeting errors, and that better guidance should be provided to communities if the policy objective is to select low per capita consumption individuals.

The third essay investigate whether cash transfers induce investments in assets and productive activities that survive the termination of program payments using data from an unconditional cash transfer project in Niger 18 months after its termination. Based on quasi-experimental methods, results indicate that local saving/credit systems (*tontines*) participation and livestock ownership significantly increased among project participants. There is also evidence of improvement in private assets, micro-enterprises and agriculture. The findings imply that cash transfer programs can have long-term sustainable impacts in rural SSA.

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Three Essays on Poverty in Sub-Saharan Africa: Multidimensional Poverty Change in Zimbabwe; Long-Term Impact of Cash Transfers in Niger; and Targeting Efficiency of Social Protection Programs in Cameroon

INTRODUCTION

In the last decades, the fight against poverty has become central in the development sector. Poverty alleviation is now seen both as instrumental for achieving sustainable economic development, and as an important overall objective of development efforts. While other regions of the world have seen absolute poverty decline quickly in the last 30 years, poverty has been rising in the 80s and 90s in Sub-Saharan Africa (SSA) where economies have not grown rapidly (Collier 2007). Recent years have brought more optimism for both growth and poverty reduction, but these recent improvements need to be confirmed, generalized, and sustained (McKay 2013, Chen and Ravallion 2010). Even in countries where growth has been present in the 2000s, poverty has not necessary decreased: in Cameroon, it remained around 39% between 2001 and 2007 (Stoeffler, Nguetse-Tegoum, and Mills 2013). For these reasons, international donors and national governments in SSA have intensified interventions targeting poor households specifically.

This focus on poverty alleviation has been accompanied by the rise of the social protection programs in developing countries. There is now a wide recognition that risk and shocks, at the household and national levels, affect individuals critically (World Bank Group 2013). Recent illustrations in SSA include droughts in Niger, rise of food prices in Cameroon, or hyperinflation and political crises in Zimbabwe. In this context, social safety nets, and in particular cash transfers, have spread rapidly from Latin America, where cash transfers originated in the 1990s, to SSA in the 2000s. Indeed, it is increasing recognized that protecting households against uninsured risk can promote household human and physical capital investments and support sustainable pathways out of poverty. This idea is latent to each essay of this dissertation, which study how individuals are affected by economics shocks; how it is possible to reach the poorest households to help them build resilience; and how social safety nets interventions supports households in their efforts to exit poverty.

The rising concern for poverty alleviation in general, and for building social safety nets that effectively address poverty in particular, leads to new questions regarding: i) the definition and measurement of poverty; ii) the targeting of poor households; and ii) the impact of poverty alleviation intervention. The three essays of this dissertation speak to these questions, by empirically investigating the following three topics: How multidimensional poverty has changed in Zimbabwe before, during and after the peak of the 2007-2008 hyperinflation crisis? How efficiently Proxy Means Testing (PMT) and community targeting identify the poor in northern Cameroon? What is the long-term impact of a cash transfer project on household investments in rural Niger 18 months after project termination? Each of these essays is an empirical application which focuses on particular events (in Zimbabwe) or projects (in Cameroon and Niger). They arise from an inductive approach, built on the belief that micro-analyses, carefully executed and examined in perspective with other similar studies in other countries or contexts are well suited for fruitfully generating conceptual knowledge and leading to new innovative programs and policies that better meet the needs of poor households. These case-studies thus contribute to the thin evidence base(s) in Sub-Saharan Africa, where poverty analyses and impact evaluations are spreading but are still subject to many challenges, including data collection. In doing so, the three essays also contribute to the broad economic thinking about poverty and poverty alleviation, while providing concrete policy recommendations to guide policy makers.

The first essay explores poverty changes in Zimbabwe in a period of acute economic, political and social crisis. In particular, it tracks multidimensional poverty changes over time before, during and after the peak of the economic crisis (hyperinflation) in 2007-2008. The essay analyzes unique nationally representative datasets collected by the Zimbabwe National Statistics Agency (ZIMSTAT) in 2001, 2007 and 2011/12, which represented the opportunity to measure how the crisis affected poverty in 2007 and how poverty evolved during the (relative) recovery after 2008. This investigation extends previous poverty analyses in Zimbabwe conducted at Virginia Tech (Alwang, Mills, and Taruvinga 2002, Larochelle 2011). First, by taking advantage of the 2011/12 dataset, it constitutes one of the first studies to measure the effect of the recovery period, thus offering a broader view of how Zimbabwean households respond to a tremendous shock like the hyperinflation crisis as they go into and emerge from the crisis. Second, the study measures deprivation across multiple dimensions, offering a more complex and nuanced picture of changes in individuals' well-being. Employing a novel multidimensional poverty index methodology developed by Alkire and Foster (2011) offers several advantages conceptually (Sen 1999) and also allows the study to overcome technical limitations, in that the measurement of money-metric poverty is impossible for the 2007 dataset in a context of hyperinflation. The Alkire-Foster methodology, on the other hand, is applicable since it constructs a multidimensional index by aggregating deprivations in several dimensions which were still measurable in 2007: education, health, employment (urban areas), housing conditions, living conditions, physical belongings, agricultural assets (rural areas), and access to services.

The results tell an interesting story. First, both the hyperinflation crisis and the recovery period appeared to have had a clear effect on individual well-being, since poverty significantly increased from 2001 to 2007, and then significantly decreased from 2007 to 2012. Second, changes vary greatly across dimensions and living areas, following distinct patterns. For instance, access to electricity improved in each period for rural areas, while in urban areas it deteriorated during the crisis and partially recovered in 2011. In particular, dimensions which have not improved during the recovery period are health and access to clean water, suggesting the need for targeted interventions in these sectors. More generally, results illustrate how an acute macroeconomic shock affects individual well-being. Because not all dimensions have recovered equally, the results also suggest a need for social assistance programs to both assisting poor households when the crisis occurs, and also sustain support across slow recovering dimension in the medium-term, while promoting resilience to future shocks in the long-term.

The second essay of the dissertation examines a pilot project of a large-scale social safety nets program in Cameroon, in order to assess its ex-post efficiency to reach poor households. The study compares two targeting methods employed in the pilot simultaneously, PMT and community-based targeting (CBT). These are the two most popular targeting methods in SSA. Indeed, targeting the poor accurately and efficiently is central to any poverty alleviation policy, and it becomes particularly crucial for building well-functioning social safety nets systems. However, because poverty is neither readily defined nor easily observable, there exist important challenges both at the operational level (targeting mechanisms) and at the analysis level (methodology to evaluate targeting). For these reasons, the choice of targeting methods has generated significant debates in the development community among stakeholders, policy makers and academics (Grosh et al. 2008, Mkandawire 2005). The objective of this essay is to contribute to the thin evidence-base on targeting efficiency, since few analyses have compared PMT and community targeting for a unique development project – and even less in SSA. To do so, the paper analyzes data collected among 1,758 households in Soulédé-Roua (where the pilot operates), with information on many dimensions (health, education, shocks, assets, consumption, etc.). Employing various existing and new indices of targeting efficiency (such as inclusion and exclusion errors), it assesses the efficiency of the two targeting methods in selecting the poorest households. In addition, the paper explores potentially different factors associated with erroneous beneficiary inclusion and exclusion for PMT and CBT.

While not fully generalizable to other contexts, the results do illustrate the potential of PMT and community targeting in an extremely poor (the pilot selected the poorest area of Cameroon), rural, Sub-Saharan African context. These results show that PMT targeting clearly dominates community targeting for selecting households with low per capita consumption. According to this monetary-based definition of poverty, community targeting performs poorly (i.e. worse than random targeting). Results also suggest that the community selects households based a different conception of poverty (rather than per capita consumption only), choosing in particular small, isolated households with low physical and human capital. However, when different poverty definitions are used to assess its targeting efficiency, community targeting still performs poorly. This suggests that communities, in this context, produced variable targeting outcomes, and are not likely to select a consistent type of households in the absence of better guidance and supervision. PMT targeting works better than the hybrid targeting employed in the project to select about 35% of the households, but targeting errors remain high (above 40%). Overall, these results question the potential for efficient identification of the poorest households in a context of very high levels of poverty and call for the development of rigorous methodologies to assess community targeting.

The third essay studies a similar unconditional cash transfer project in rural Niger, with a different angle: it explores investments in durable assets by beneficiary households. While the previous essay scrutinizes data collected before transfers started (baseline data), this third essay is based on an original dataset collected 18 months after project termination to capture long-term effects of the cash transfers. Indeed, there is emerging empirical evidence from Latin America that beneficiaries from such programs, rather than spending their entire transfer on consumption goods, invest significantly in productive activities (Gertler, Martinez, and Rubio-Codina 2012). In Sub-Saharan Africa, where cash transfers spread rapidly in the 2000s and where household investments in very poor, rural areas are usually extremely low, the "productive" side of cash transfers has been considered promising, but the evidence gap remains (Barrientos 2012). In particular, very few empirical studies have investigated the sustained effect on household assets after transfers are stopped. At this point in time households have potentially realized investments and benefited from them, or on the contrary have been affected by shocks and disinvested.

To explore this question of long-term productive investments, we collected data among 1,579 households which were beneficiaries and non-beneficiaries from the pilot cash transfer project in rural Niger, 18 months after project termination (now in the scale-up phase in other areas of the country). To draw causal inference from these empirical data, the main identification strategy relies on quasi-experimental methods, exploiting the design of the project. Indeed, the pilot selected 30% of beneficiaries in each of the 52 villages using a PMT targeting method, with the consequence that the PMT eligibility threshold varies by village. This variation in eligibility threshold makes it possible to compare beneficiary to non-beneficiaries with similar PMT scores, but different eligibility status. These non-beneficiaries constitute a credible counterfactual to study the impact of the project.

Results show a significant impact of the project on tontines (local saving and credit systems) participation, which was strongly encouraged during the project, and remained after the project stopped. Moreover, the project led to an increase of livestock ownership by about 0.3 Tropical Livestock Units (TLU), and there is evidence of improvement in private assets, living standards, micro-enterprises and agriculture. Altogether, these findings are encouraging regarding the long-term productive impact of cash transfer projects and call for further studies on how these investments translate into long-term improvement in other aspects of well-being.

Overall, by studying different facets of poverty in Sub-Saharan Africa and carefully analyzing datasets from three different countries, the three essays in this dissertation shed light on three crucial issues for poverty alleviation: poverty measurement, targeting of the poor, and anti-poverty impact. A source for concern (and a motivation for further research) is that at the end of this dissertation, the question of poverty definition, present at the origin of all three papers, remains. Yet, an even greater source for optimism is that all three papers, in different ways, from the modest post-crisis recovery in Zimbabwe to poverty simulations in Cameroon to impact on household investments in Niger, point towards poverty reduction in Sub-Saharan Africa. After many years of afro-pessimism, I hope that this work contributes to help practitioners, policy makers, and academics find positive future pathways of poverty alleviation efforts.

References

Alkire, Sabina, and James Foster. 2011. "Counting and multidimensional poverty measurement." *Journal of Public Economics* no. 95 (7):476-487.

Alwang, Jeffrey, Bradford F Mills, and Nelson Taruvinga. 2002. *Why has poverty increased in Zimbabwe?*: World Bank Publications.

Barrientos, Armando. 2012. "Social Transfers and Growth: What do we know? What do we need to find out?" *World Development* no. 40 (1):11-20.

Chen, Shaohua, and Martin Ravallion. 2010. "The developing world is poorer than we thought, but no less successful in the fight against poverty." *The Quarterly Journal of Economics* no. 125 (4):1577-1625.

Collier, Paul. 2007. "Poverty reduction in Africa." *Proceedings of the National Academy of Sciences* no. 104 (43):16763-16768.

Gertler, P.J., S.W. Martinez, and M. Rubio-Codina. 2012. "Investing Cash Transfers to Raise Long-Term Living Standards." *American Economic Journal: Applied Economics* no. 4 (1):164-192.

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

Larochelle, Catherine. 2011. *Three essays on productivity and risk, marketing decisions, and changes in well-being over time*, Virginia Polytechnic Institute and State University.

McKay, Andy. 2013. "Growth and Poverty Reduction in Africa in the Last Two Decades: Evidence from an AERC Growth-Poverty Project and Beyond." *Journal of African Economies* no. 22 (suppl 1):i49-i76.

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

Sen, Amartya. 1999. *Development as freedom*: Oxford University Press.

Stoeffler, Q., P. Nguetse-Tegoum, and B. Mills. 2013. "Generating a System for Targeting Unconditional Cash Transfers in Cameroun." In *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*, edited by Carlo del Ninno and Bradford Mills. Washington, DC: World Bank.

World Bank Group. 2013. *World Development Report 2014: Risk and Opportunity-Managing Risk for Development*: World Bank Publications.

ESSAY 1: Multidimensional poverty in crisis: lessons from Zimbabwe

1 Introduction

During the first decade of the 21st century, Zimbabwe experienced a sharp social, political and economic crisis, but is now on a recovery path (Besada and LaChapelle, 2011; Murithi and Mawadza, 2011). One of the most industrialized African economies at independence in 1980 and through the early 1990s, Zimbabwe experienced economic deterioration in the 1990s as a result of both recurring drought and economic mismanagement. This situation evolved into a full-blown social and political crisis in the late 1990s fueled by controversial land reform and rising political violence. From 1999 to 2007 Zimbabwe experienced negative economic growth and rising inflation along with the collapse of the commercial agriculture, tourism and manufacturing sectors (Robertson, 2011). The paroxysm of the crisis was reached in 2007 with hyperinflation reaching 231 million percent officially (Makochekanwa and Kambarami, 2011).[1] In a move toward stabilization, the economy was dollarized and a Global Political Agreement (GPA) between the two principal political parties was ratified in September 2008. Since February 2009, the country has been led by a Government of National Unity (GNU), inflation has been under control and economic growth has returned, although the recovery is still regarded as fragile (Richardson, 2013).[2]

The macroeconomic causes and the economy-wide impact of the 2000s crisis have been documented (Hanke, 2012; Mashakada, 2013; Ndlela, 2011), along with the impact of the land reform on well-being of different household groupings (Scoones et al., 2010). However the

[1] Economists have evaluated that yearly hyperinflation reached 65 followed by 107 zeros in mid-november 2008, which means that prices doubled every 24.7 hours (Hanke, 2008; Hanke & Kwok, 2009).

[2] In particular, GPD per capita (in 2005 constant USD) was 681 in 2001, 345 in 2008 and 431 in 2012; after 7 years of negative growth, Zimbabwe's annual GDP growth was between 4.4 and 10.6% between 2009 and 2012, but slowing down (http://data.worldbank.org/country/zimbabwe).

evolution of household well-being and its different dimensions during and after the crisis has not been fully investigated. It is unclear how the economic crisis and subsequent recovery impacted various dimensions of household well-being such as access to education and public services, health, or income/consumption. The paper fills this gap by analyzing changes in multidimensional indicators of poverty between 2001, 2007 and 2011/12 using the nationally representative household Incomes, Consumption and Expenditure Surveys (ICES) and Poverty, Income, Consumption and Expenditure Survey (PICES).

The rise of poverty in Zimbabwe was already a concern in the 1990s due to a combination of economic decline, severe drought and ill-effects of poor governance (Marquette, 1997; Potts and Mutambirwa, 1998). Studies based on nationally representative household surveys (ICES of 1990/91 and 1995/96) conducted by the Central Statistical Office (CSO)[3] show an increase in poverty during the first-half of the decade (CSO, 1998). Savings and household asset bases were negatively affected through their use as coping mechanisms in response to recurring economic and environmental stress (Ersado, Alderman, and Alwang, 2003). Limited safety nets and income diversification have not been sufficient to help farmers cope with shocks in semi-arid areas, especially in remote and excluded areas (Bird and Shepherd, 2003). A decomposition of poverty increases between 1990 and 1996 shows that a deterioration of the entire economy was the main driver, while household coping strategies partially offset the general deterioration in economic conditions (Alwang, Mills, and Taruvinga, 2002a, 2002b). A study based on the 2001 and 2007 ICES datasets show increases in asset poverty in the 2000s (Larochelle, Alwang, and Taruvinga, 2014).

Most previous studies of poverty in Zimbabwe used a unidimensional money-metric measure (ZIMSTAT, 2013). However, money-metric poverty measures do not reflect all factors affecting

[3] The CSO is called ZIMSTAT today.

well-being (Duclos, Sahn, and Younger, 2006b; Reddy and Pogge, 2009; Reddy, Visaria, and Asali, 2006; Sen, 1999). Money-metric measures also face technical challenges with respect to the choice and construction of the poverty measure, particularly in terms of the proper deflator when making spatial and inter-temporal comparisons (Laderchi, Saith, and Stewart, 2003). In Zimbabwe, establishment of a money-metric poverty measure is particularly problematic because of the hyperinflation, which makes valuation of consumption expenditures using available national surveys impossible in 2007.

A multidimensional poverty index is an attractive alternative and complement to money-metric approaches. The literature increasingly recognizes the multidimensional nature of poverty. Since the seminal work of Amartya Sen, a large literature using the capability approach to conceptualize and measure poverty has emerged (Sen, 1985, 1993, 1999). The capability approach considers poverty as a lack of capability to achieve critical “functioning” in essential dimensions of well-being. These dimensions include food, health, education, electricity, human rights and security. Households lacking capability in a given dimension are said to suffer from depravation in that dimension. In practice, authors have considered a wide range of dimensions. For instance, household expenditures and children’s height-for-age have been used jointly to compare three African countries (Duclos et al., 2006b). A Multidimensional Poverty Index (MPI) has been constructed for 104 countries from ten indicators corresponding to three dimensions: education, health and standard of living (Alkire and Santos, 2011). These papers show that the poverty orderings of regions or countries based on multidimensional indices often contrast with orderings based on unidimensional or money-metric measures.[4]

[4] For instance, an income poor household in China has 68% probability to be multidimensionally non-poor; an income non-poor in Chad has 59% probability to be multidimensionally poor (Alkire & Santos, 2011).

The purpose of this paper is to cast additional information on changes in individual welfare during the crises in two ways: first, by computing poverty changes even in a context of hyperinflation when price data are unreliable; second, by decomposing overall changes into changes in the underlying depravation dimensions. Zimbabwe constitutes a particularly interesting case to study changes in well-being along multiple dimensions because households have been affected by an acute economic and social crisis, followed by a recovery. Changes in well-being did not shift uniformly along all dimensions during this period: for instance, access to electricity and some human capital indicators actually improved through the 2000s. In contrast, health indicators and ownership of livestock in rural area declined over the same period, while access to services declined and then recovered.

Multidimensional indices aggregate deprivations encountered by individuals to form a picture of the complex evolution of poverty from 2001 to 2011/12. The multidimensional index employed in this paper, based on the Alkire-Foster (A-F) methodology (Alkire and Foster, 2011a), is decomposed by dimension and by geographic area to identify key factors shifting individuals deprivation. The results show a clear increase in multidimensional poverty from 2001 to 2007, and then a decrease from 2007 to 2011/12, leaving an ambiguous overall change in poverty from 2001 to 2011/12. However, as noted, changes in particular dimensions did not necessarily follow the overall trend. The results are robustly observed when using alternative specifications and multidimensional measures.

The next section presents and justifies the choice of the main A-F multidimensional poverty index. Section 3 presents the data, the dimensions chosen and the construction of the Zimbabwe A-F index. Section 4 presents results and compares them to a money-metric poverty measure. Section 5 tests index robustness. The last section concludes and distills policy implications.

2 Multidimensional indices

There is growing agreement regarding the multidimensional nature of poverty, but substantial debate rages about the way to conceptualize and measure these dimensions (Alkire and Foster, 2011b; Atkinson, 2003; Datt, 2013; Ferreira and Lugo, 2012; Ravallion, 2011). The choice of measure does matter and can change the characterization of poverty in terms of both levels and changes (Deutsch and Silber, 2005; Duclos, Sahn, and Younger, 2006a; Laderchi, Saith, and Stewart, 2003). A multidimensional measure using a single index is an intermediate between unidimensional measures of poverty such as money-metric poverty, and a "dashboard" approach (CMEPSP, Stiglitz, Sen, and Fitoussi, 2009) which considers in parallel and compares separately (over space and time) a series of indicators. Reasons to employ a single multidimensional index rather than a dashboard approach include simplicity (obtaining a clear trend) and accounting for the joint distribution of deprivations. Decompositions of the multidimensional index also allow identification of how changes in individual dimensions contribute to overall index change.

A large literature has now emerged on multidimensional poverty. Theoretical studies have followed an axiomatic approach to generate indices consisting of multiple dimensions which satisfy sets of desirable properties (Bourguignon and Chakravarty, 2003; Tsui, 2002). Two issues must be addressed in empirical application: (i) What is the cutoff below which a person is said to be deprived?, and (ii) When considering the aggregation of depravations, how to "add them up" to generate an overall picture of poverty. The latter decision usually involves either a "union approach" (an individual is poor if deprived in one dimension) or an "intersection approach" (an individual is poor if deprived in all dimensions). The "counting approach" is an intermediate: it considers an individual as poor if deprived in k dimensions, with k between 1 (the union approach) and all dimensions (the intersection approach) (Alkire and Foster, 2011a). All approaches entail normative judgments on the choice of dimensions, deprivation thresholds, and level of k in empirical application. Statistical methods, including Multiple Correspondence Analysis, have been explored to reduce perceived “arbitrariness” (Asselin, 2002; Ezzrari and Verme, 2012; Njong and Ningaye, 2008). Several indices are often used in parallel when making comparisons across countries or over time, in order to demonstrate robustness of the results (Deutsch and Silber, 2005; Duclos et al., 2006b).

Poverty measurement consists of two steps: 1) identification of poor individuals or households[5]; and 2) aggregation of the poor into a single index. In the context of multidimensional poverty, the first step can be decomposed into: i) identifying deprivation of individuals in each dimension; ii) given individual dimensional deprivations, identifying poor individuals. Identification of the poor thus takes into account *m* dimensions of achievement vectors $y \in R^{m}{}_{+}$ where y_j is for instance the level of education. Define for each dimension j, a deprivation cutoff $z \in R^{m}{}_{++}$, such that an individual i is poor (or deprived) in dimension j if $y_{ij} < z_j$. Dimensions are then combined through an identification function ρ such that $\rho(y,z) = 1$ if an individual is multidimensionally poor and $\rho(y,z) = 0$ if an individual is not poor. A simple identification function is the “*union” function*:

$$\rho(y,z) = 1 \text{ if } y_{ij} < z_j \text{ for any dimension } j \tag{1}$$

$$\rho(y,z) = 0 \text{ otherwise} \tag{2}$$

A corresponding simple aggregation method would be given by the number of poor H:

$$H = \sum_{i}^{n} \rho(y_i, z) \tag{3}$$

[5] We focus on identification of deprivation for individuals in the household.

Alkire and Foster (2011a) focus on a single measure which is a generalization of the counting approach and an adaptation of the FGT poverty index (Foster, Greer and Thorbecke, 1984).[6] The method uses a double cutoff in the identification step: individual i is deprived in dimension j if its achievement y_{ij} is inferior to the deprivation threshold z_j; then, individual i is considered as poor if the weighted sum of its deprived dimensions c_i is greater than a poverty threshold k. The A-F multidimensional poverty index M_0 is simply the product of the headcount ratio of poor individuals H and the average deprivation share among the poor A:

$$M_0 = H * A \tag{4}$$

The general class of A-F multidimensional poverty measures M_α is defined from the weighted censored matrix of achievements $g^\propto(k)$. Let $g^{\propto\prime}$ be the matrix of achievements, with a typical element $g_{ij}^{\propto\prime} = 0$ if the individual is not deprived in this dimension and $g_{ij}^{\propto\prime} = (\frac{z_j - y_{ij}}{z_j})^\propto$ if the individual is deprived in this dimension. The weighted censored matrix of achievements $g^\propto(k)$ is obtained by applying weights w_j to each dimension and by censoring at k, i.e. replacing $g_{ij}^{\propto\prime} = 0$ if the individual is not poor ($c_i < k$). Then:

$$M_\propto = \mu\left(g^\propto(k)\right) \text{ for } \propto \geq 0 \tag{5}$$

In particular, M_1 is the multidimensional adjusted poverty gap, and M_2 is the multidimensional adjusted poverty severity.

This measure of multidimensional poverty $M_\propto$ has several advantages. First, it satisfies useful properties (see Theorem 1, Alkire and Foster, 2011a) including (i) poverty focus, which means that an improvement among the non-poor i does not affect $M_\propto$ (whether or not i is deprived in j); (ii) deprivation focus, which means that an improvement for i in a non-deprived dimension j (whether or not i is poor) does not affect $M_\propto$; and (iii) decomposability, which allows poverty

[6] For more details about the methodology, see the Technical Appendix and Alkire and Foster (2011).

decomposition by region or by group. Also, the counting approach (in particular M_0) is applicable to ordinal variables, which is a crucial characteristic since deprivation variables frequently take an ordinal form (Bossert, Chakravarty, and D'Ambrosio, 2012). Finally, it is quite intuitive and suits applications where there are many dimensions. For these reasons, the counting approach was widely used before being formalized (Gordon, Nandy, Pantazis, Pemberton, and Townsend, 2004; Mack and Lansley, 1985; Vranken, 2002).

3 Data and empirical approach

A. Data

The data used in this paper come from three nationally representative household surveys conducted by ZIMSTAT: the Incomes, Consumption and Expenditure Surveys (ICES) from January to December 2001 and from July 2007 to December 2007[7] and the Poverty, Incomes, Consumption and Expenditure Surveys (PICES) from June 2011 to May 2012. The ICES/PICES surveys are well suited to construct multidimensional indices, because they include information at the household and individual level, and were collected in a consistent manner. The surveys were conducted in the eight provinces of Zimbabwe and in the cities of Harare and Bulawayo. The number of usable observations (households) is 19,941 in 2001 (12,575 rural, 7,366 urban), 14,112 in 2007 (11,716 rural, 2,396 urban) and 29,765 in 2011/12 (24,723 rural, 5,042 urban). Survey weights and household size are employed to obtain nationally representative figures, including the urban/rural proportions.[8] ICES/PICES questionnaires include modules on

[7] The 2007/8 ICES survey was conducted from July 2007 to June 2008, but due to the economic crisis, most interviews planned in 2008 were not conducted. The few observations from 2008 are discarded because of the poor reliability of these data.

[8] When using survey weights, the total population is 11.3 million in 2001 (7.8 million rural, 3.4 million urban), 11.0 million in 2007 (8.0 million rural and 3.0 million urban) and 11.9 million in 2011 (8.8 million rural and 3.1 million urban). The slight decrease in urban population between 2001 and 2007 may be due to the new sample frame used for 2007/08 and 2011/12 (based on a new population survey conducted in 2002), but is not inconsistent with evidence from Zimbabwe and elsewhere (Potts, 2006, 2009).

expenditures that can be employed in a money-metric measure, but the 2007 expenditures are unreliable because of hyperinflation during the period. All modules are virtually identical and available for the three years. They include information on household demographics, education, employment, health care, migration, housing characteristics, assets ownership, access to services, enterprises, and agricultural activities.

B. Choice of dimensions, cutoffs and weights

There is a substantial debate regarding the choice of dimensions and the assignment of weights to each dimension in the multidimensional poverty measurement literature (Alkire, 2007; Ravallion, 2011). In this paper, these choices are made normatively (Alkire and Santos, 2011; Gallo and Roche, 2013) and deprivation variables reflect the Zimbabwean context, as well as the different meaning of deprivations in urban and rural areas (Table 1).[9] Eight dimensions (education, health, employment, housing conditions, living conditions, assets, agricultural assets and access to services) are used because of their importance as capabilities to attain essential functioning of well-being, intrinsically and instrumentally (Alkire, 2007). For each dimension, one or several variables are used, driven by their relevance as indicators of deprivation and by data availability. Weights are assigned normatively to dimensions, and then to each variable.[10] Thresholds are chosen to be conservative, in that they correspond to very low levels of achievement (e.g. finishing primary school, having any type of toilet in rural areas). Robustness tests are conducted regarding the impact of the choice of variables, cutoffs and weights (see

[9] Ideally, we would have liked to embrace a participatory approach in the choice of dimensions and weights (Alkire, 2007; Garcia & Ritterbush, 2013; Robeyns, 2005) or have access to data on what citizens consider necessary in order to live a decent life (Bossert et al., 2009). When appropriate, variables and thresholds commonly used in the Millennium Development Goals (MDG) and multidimensional literatures were used here, as well as those of the MPI.

[10] Variable weights are either 0.5 or 1 to facilitate the intuitive interpretation of the A-F indicator, following the recommendations of Atkinson et al. (2002) p25: "the interpretation of the set of indicators is greatly eased where the individual components have degrees of importance that, while not necessarily exactly equal, are not grossly different".

section 5). The variables employed in each dimension are now described in more detail. Table 1 provides an overview of the dimension variables and weights employed.

Education and *health* are essential elements of an individual's human capital and necessary to live a fulfilling life and to succeed personally and professionally. The weights of 2 associated with each of these dimensions reflect their importance in household well-being and the weight given to these sectors by the Zimbabwean government from independence and until now (Bird and Shepherd, 2003; CSO, 1998; ZIMSTAT, 2013). Indicators of levels of education are: the absence in the household of anyone who has completed primary education, and the presence of a primary school-aged child in the household not being sent to school.[11] Economic and social deprivations clearly impact health outcomes in Zimbabwe (Watts et al., 2007). Variables chosen as health indicators are the presence of a chronically ill individual in the household, and a household member having been ill without getting health care.[12] In times of crisis, the causes of the changes in these health and education dimensions are likely to be found both on the demand and supply sides: households can become unable to pay for health care, or facilities can close.

Unemployment is associated with poverty in urban Zimbabwe (Hamdok, 1999; Mpofu, 2011). An urban household is considered as deprived in this dimension when a household member records "unemployment" as its *main* occupation over the last 12 months. Because unemployment is less common and is more difficult to identify in rural areas it is not included in the rural measure.[13]

[11] This may be due to a delay in enrollment, which affects achievement (Larochelle & Alwang, 2012), or because the child dropped out before finishing primary school.

[12] The recall period for health data is 30 days.

[13] This unemployment indicator does not fully reflect the changes which are likely to occur in the labor market, including partial unemployment and forced transition to less remunerative occupations.

Housing and *living conditions* are direct essential reflections of well-being but also instrumental in contributing to improved health, work, and education outcomes.[14] For rural areas, a weight of one (1) is attributed to each of these two dimensions, equivalent to a weight of 0.5 to each of the four variables. In urban areas, where lack of electricity indicates a greater state of deprivation, a weight of 1 is attributed to the lack of electricity, which is why housing conditions obtain an overall weight of 1.5. Households are considered deprived if they lack access to electricity and if the house has no toilet (in rural areas) or no flush toilet (in urban areas, where sanitation is more developed). For living conditions, households in rural areas are deprived if their main source of water is an unprotected well, a river or another unprotected source, or if the source of water is 1km away or farther. In urban areas, because water infrastructure is more developed, deprivation is defined as not having access to piped water or communal water on premise. Finally, households are deprived if they use wood or “other” (not electricity, paraffin, gas, coal) as cooking fuel. These variables and the thresholds chosen are commonly used in the MDG and multidimensional poverty literatures (Alkire and Santos, 2011; Njong and Ningaye, 2008). Household physical assets are indicative of a higher level of well-being and are reflective of capability to function. Household asset stocks across a variety of assets are accounted for through a physical asset index (PAI) and an asset deprivation (D) threshold as follows:

$$PAI = 2 * motor\ vehicule + motorcycle + bicycle + television + radio + fridge + landline\ phone$$

$$D = 1\ if\ PAI < 2$$

Thus, households are *not* deprived if they own a car or if they have at least two of the other assets. This index is identical to the one used in the MPI (Alkire and Santos, 2011) and gives a

[14] For instance, the use of wood as cooking fuel is considered as a major health threat, mostly because of the respiratory illness it causes (Boadi & Kuitunen, 2006; Ellegård, 1996; Rehfuess, Mehta, & Prüss-Üstün, 2006).

simple and intuitive measure of physical asset deprivation.[15] The asset index is robust to use of an index based on different item weights and one constructed using Multiple Correspondence Analysis (MCA) to determine weights (see Booysen, Van Der Berg, Burger, Maltitz, and Rand, 2008 for details on MCA).

For rural households, agricultural assets are essential indicators of well-being and capabilities related to agricultural activity. The agricultural asset dimension is only employed in rural areas. Three variables are each given a weight of 0.5 for this dimension. The first variable is land, whose lack is associated with poverty in rural Zimbabwe (Hamdok, 1999). The threshold used (0.25 hectares) is sufficiently low to represent effective deprivation of land. The second variable, livestock measured in Tropical Livestock Units (TLU)[16], is an indicator of wealth in rural areas that can be used to insulate households from the impact of shocks (Mushongah, 2009). A TLU deprivation threshold of 1 indicates very low levels of livestock assets. The third variable for this dimension is rural equipment, which is associated with well-being in rural areas and enhances productivity of farmers. An agricultural equipment index (AEI) is created as follows:

$$AEI = plough + \ wheelbarrow \ + \ scotchcart \ + \ tractor \ + \ griding\_mill$$

$$D = 1 \ if \ AEI < 1$$

The final dimension of well-being is geographic access to services, where deprivation indicates remoteness from the services. Distance to seven services is available in the data and households are considered to be deprived if they are far from 2 or more services. The distance thresholds employed are 5km for a primary school, 15km for a secondary school, 15km for a hospital, 5km

[15] The difference is that we consider only landline phones, because the change in cellphone ownership due to technological transformations between 2001 and 2011 would introduce a bias in the index.

[16] The TLU index used, adapted to the data available, is computed as follow:

$$TLU = 1 * (cows + bulls + oxen) + 0.8 * calves + 0.8 * ostriches + 0.5 * pigs + 0.25 * (sheeps + goats) + 0.1 * (geese + turkeys + ducks) + 0.05 * (chicken + pigeons + other\ poultry) + 0.5 * donkey + 0.25 * other\ livestock$$

for shops, 5km for a hammer mill, 15km for a post office, and 5km for a bus stop. These distance thresholds are halved in urban areas, where services tend to be closer but distance still represents a barrier to access (e.g. transaction cost). In addition, the lack of essential services close to the household's residence indicates remoteness of the neighborhood (or perhaps its neglect by the local government).

Ideally, the indices should be constructed at the individual, rather than household level. However, only 4 variables vary among individuals in the household. Further, there are clear intra-household externalities from many dimensions of individual well-being and most household-level variables also reflect individual capabilities, especially with respect to housing and living conditions. Thus, deprivation status is assessed at the household level and then weighted by the household size to obtain poverty indices in terms of individuals.

Several changes were made in the way the A-F method is usually applied to account for the Zimbabwe context and data. First, either different variables were used in urban and rural areas or different weights are applied for the same variable. Therefore, the index acknowledges the different nature of poverty in an urban or rural environment. Second, different thresholds were used in urban and rural areas for a few variables. Third, larger households are more likely to be deprived in individual dimensions, such as having a chronically ill member, because they include more members. Consequently, M_α was adjusted so that household size does not mechanically increase or decrease the likelihood that a household is deprived in any dimension. Fourth, when possible, cardinal variables were generated from ordinal ones (creation of indices) to facilitate computation of M_1 and M_2. Fifth, as noted in section 2, indicator variables (0/1) weight more heavily than other ordinal variables in M_1 and M_2. Thus, weights were adjusted accordingly in our M_1 and M_2 measure to correspond to the original weights of indicator and not-indicator variables. The detail of these modifications is given in the Technical Appendix and results are robust to the exclusion of these adjustments.

C. Descriptive statistics

Table 2 shows the number of individuals indicated as deprived for each variable (raw headcounts).[17] Four types of change occur between 2001, 2007 and 2011/12, highlighting the variability of changes in indicators of well-being across dimensions. First, some variables are stable over the period: unemployment and the lack of access to toilets. Second, several indicators are responsive to the crisis and the recovery: they worsen from 2001 to 2007, but they rebound from 2007 to 2011/12. These responsive indicators are children not enrolled in school; use of wood as cooking fuel; rural agricultural equipment; and access to services. Thirdly, some dimensions show a declining trend over the entire period: the two health variables; access to protected water; and livestock ownership. Some indicators show improvement at each period: the proportion of individuals from households with members having achieved at least 7 years of education; access to electricity; and household physical assets ownership.[18] Some changes vary by area: while access to electricity or toilet was relatively good in urban areas in 2001, it declined in 2007 – and also in 2011/12 for access to toilet.[19] Rural areas tended to continue a long-term improvement in electricity, toilet and cooking fuel. The increase in distance to services observed in 2007 is due to changes in rural areas only.

[17] Only observations without any missing variable are kept: 19,790 observations in 2001, 13,049 in 2007 and 28,935 in 2011. For more details about the treatment of missing variables, see the Technical Appendix.
[18] Land ownership deprivation increased in 2007 (but not significantly) and decreased significantly in 2011/12.
[19] The data show a significant change in deprivation in educational attainment in urban areas in 2011/12. One a possible explanation is that some of the least educated households left the cities when economic opportunities became meager during the peak of the crisis (Potts, 2006, 2009). This would be consistent with the small *decrease* in urban poverty from 2001 to 2007 found by Larochelle et al. (2014).

These changes in indicators are consistent with evidence from other sources. Schooling seems to have resisted the crisis relatively well (Larochelle et al., 2014) and improved recently (UNZ, 2012). Recent reports have noted the need for access to clean water and sanitation (Makochekanwa and Kwaramba, 2010; OPHI, 2013; UNZ, 2012). The decline in access to protected water is noted to be particularly acute in urban areas with the rapid deterioration of the water distribution system (AMCOW, 2010; Makochekanwa and Kwaramba, 2010). Overall, rural households have increased land size over the period, partly due to redistribution of lands in the former large-scale commercial farming areas (Moyo, 2011; Scoones et al., 2012). According to our data, the decrease in land deprivation was important in large scale commercial farming areas, but land deprivation actually *increased* in communal and resettlement areas between 2001 and 2007. An interesting finding is the large increase in the proportion of individuals far from essential services in 2007, followed by an improvement of the situation in 2011/12. This finding suggests that some of these services closed between 2001 and 2007 to reopen after the paroxysm of the crisis. While the magnitude of the change may seem unlikely given the rather short period, other empirical accounts support the findings. Access to social services appears to have declined from 2000 to 2008 (Makochekanwa and Kwaramba, 2010; Nyazema, 2010) but an improvement was observed from 2009 to 2012 (Shamu, 2012; UNZ, 2012). The crisis temporarily affected the functioning of hammer mills (NMottsConsulting, 2004) and there is anecdotal evidence of shop closures and bus service interruptions.[20]

The fact that dimensions of well-being show different trends highlights the need for a multidimensional measure to capture the overall poverty evolution and explore individual

[20] See for instance: "Zimbabwean bus drivers in cells, report says" Aug 1, 2007, Deutsche Presse-Agentur (http://www.zimbabwesituation.com/aug2_2007.html#Z18); "Shops emptied as panic grips Zimbabwe", July 4, 2007, The Guardian (http://www.guardian.co.uk/world/2007/jul/05/zimbabwe.topstories3).

dimension contributions to changes. A-F multidimensional poverty index results are presented in the next section.

4 Results

Our main results come from our multidimensional poverty indices M_{α}, generated using the A-F methodology, and its different decompositions. Incidence, depth and severity of poverty are computed based on deprivation thresholds $k = 1$ to $k = 4$ (out of a weighted total of 9.5 deprivations) (Table 3). For the incidence measure M_0, the multidimensional adjusted poverty headcount ratio with $k = 3$ is 0.180 in 2001, 0.216 in 2007 and 0.192 in 2011/12.[21] For all levels of k, there is a clear and significant increase in multi-dimensional poverty between 2001 and 2007 (+20.1% for $k = 3$).[22] This is consistent with previous studies (Larochelle et al., 2014) and with the fact that 2007-2008 corresponds to the worst period of the crisis. Consistent with the recovery of the Zimbabwe economy after 2008, findings show a clear and significant decrease in poverty incidence between 2007 and 2011/12 for all levels of k (-11.4% for $k = 3$). Overall, the multidimensional poverty incidence is higher in 2011/12 than it was in 2001, and the change between the two periods is small but significant at any k (+6.4% for $k = 3$). This finding suggests that the recovery period ameliorated the adverse effects of the economic crisis in aggregate across multiple dimensions, but that the effect of the crisis on poverty is still tangible four years into recovery.

[21] M_0 is usually much lower than poverty headcount ratios based on a money-metric measure (to which it does not compare directly) because it is the product of poor households average share of deprivations (lower or equal to 1) and the headcount ratio (which decreases when k increases). The average share of deprivations among the poor is the average number of deprivations of poor households divided by the maximum number of possible deprivations (see equation (4) and Technical Appendix).

[22] The significance of the changes was computed following Yalonetzky (2011). Confidence intervals are available upon request.

The multidimensional incidence measure is decomposed into the headcount ratio H (the proportion of poor individuals for a given k) and the average deprivation share A (the average share of deprivations of those who are poor), since $M_0 = H * A$ (Table 4). Results indicate that for all levels of k, the headcount ratio H increases between 2001 and 2007 and then decreases in 2011/12 (to a level similar to 2001). The average deprivation share A increases and then decreases as well, except for $k = 4$ for which A also increases from 2007 to 2011/12. In contrast to the headcount trend, A is higher in 2011/12 than in 2001 for all levels of k. Thus, the proportion of multidimensional poor individuals has not increased between 2001 and 2011/12, but poor individuals suffer from a higher average number of deprivations in 2011/12 compared to 2001. This higher number of depravations drives the overall increase in multidimensional poverty incidence M_0.

These findings are confirmed by the analysis of the multidimensional poverty depth and severity, M_1 and M_2 (Table 3). For all levels of k, the poverty depth M_1 clearly increases between 2001 and 2007 (+21.6% for $k = 3$) but then falls (by a smaller amount) between 2007 and 2011/12 (-14.2% for $k = 3$). A similar trend is found for the M_2 severity. Thus, similar to multidimensional poverty incidence, poverty depth and severity are significantly higher in 2011/12 than in 2001 for all k.

It is possible to break down the incidence, depth and severity measures by dimension and to show the percentage of contribution of each dimension (Table 5).[23] The decomposition shows the

[23] See the Technical Appendix. The percentage contribution to $M_\propto$ is obtained by using the decomposition in (14) and dividing by $M_\propto$, which means: $PCD_{jk}^{\propto} = \frac{\mu(g_{\cdot j}^{\propto}(k))/d}{M_{\propto k}}$. $PCD_j^{\propto}$ is computed for $k = 3$ and shows the average percentage contribution of each dimension for $\propto = 0,1,2$ (Table 5). Note that the percentage contribution differs from raw ratios of households suffering from each depravation (Table 2) because it is based only on households whose deprivations count c_i is greater or equal to k, and is presented as a percentage contribution to $M_\propto$. Therefore, an increase between periods does not necessarily mean an increase in the ratio of households suffering from this deprivation.

relative percentage share of each variable to the overall level. Results indicate that level of assets, distance to services, access to electricity and the source of cooking fuel are the greatest contributors to the multidimensional incidence measure M_0 from 2001 to 2011/12. Education, land and unemployment have low contributions to the poverty measures nationally (when urban and rural individuals are pooled together). Health and water source are not large contributors to multidimensional poverty in 2001, but become greater sources of deprivation in later periods. The multidimensional incidence, depth and severity measure (M_0, M_1 and M_2) can also be broken down by rural and urban areas. Results of this decomposition show that the decrease in multidimensional poverty from 2007 to 2011/12 was more pronounced in rural areas, while urban poverty did not significantly decrease after 2007 (table A1).[24] Consequently, poverty significantly increased from 2001 to 2011/12 in urban areas, but not in rural areas. Indeed, several dimensions continued to improve in rural areas over the period (access to electricity, toilets, use of cooking fuel other than wood). Conversely, in urban areas, some households started to lose access to these assets during the crisis or saw a greater relative decline in these dimensions (access to clean water for instance). This suggests that deprivations brought on by the crisis have not dissipated as rapidly in urban areas as in rural areas.

M_0 is further decomposed by region: 8 provinces and 2 cities, Harare and Bulawayo (table A2). Results show that changes varied significantly across the country. From 2001 and 2007, poverty *decreased* slightly or stagnated in central northern regions of Mashonaland (Central, East and West) and Midlands. The general rise in poverty during this period was driven by poverty increases in Harare and Matabeleland North and South[25], Manicaland and Masvingo. Similarly, from 2007 to 2011/12, poverty reduction tended to be higher in the regions where deprivations

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[24] Rural areas contribute to more than 80% of M_α for all years.

[25] There was also an important drought in Matabeleland in 2002, which may have also affected poverty changes.

increased the most during the previous period. However, poverty continued to increase from 2007 to 2011/12 in Bulawayo. The regions which have improved the most between 2001 and 2011/12 overall are Mashonaland (Central, East and West) and Midlands, while poverty remains high in Matabeleland (North and South) and Masvingo in 2011/12. Decomposition by land use area shows that in 2001 rural poverty levels were higher in large-scale commercial farming (LSCF) areas compared to resettlement and communal areas. From 2001 to 2011/12, poverty decreased in LSCF areas but increased in other areas. As a result, by 2011/12 poverty levels are similar across land use areas.[26]

Money-metric poverty measures are computed for comparison in 2001 and 2011/12 (this was not possible for 2007 because of hyperinflation). Figure 1 shows clearly that the distribution of per capita consumption in 2011/12 lies to the left of the distribution in 2001, indicating a broad-based decrease in well-being when measured in money-metric terms. This is confirmed by the computation of the incidence, depth and severity (money-metric) poverty measures (Table 6). For the poverty line chosen[27], the increase in poverty is large: a 6.3 percentage point increase in P_0, meaning a 9.6% increase. Further, the result is not dependent on the threshold chosen as the poverty incidence is higher for almost the entire range of possible poverty lines (Figure 2).[28] The money-metric poverty estimates are consistent with the multidimensional poverty measures which also show that poverty is higher in 2011/12 than in 2001, although the increase is poverty is greater with the money-metric estimate. However, the decomposition by urban and rural areas

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[26] Change in LSCF areas are probably due to the fact that the population surveyed in these areas changed between 2001 and 2011 in the context of the land reform. In 2001, people surveyed were probably more likely to be poor tenants, whereas in 2011 they were probably mostly land invaders. In fact in 2011 LSCF households had a larger size, more children, more women as household head, higher levels of education, and were much less likely to be permanent employee and much more likely to be own-account farmers compared to LSCF households in 2001.

[27] For comparison purposes, a poverty line is defined so that $P_0 = H \text{ for } k = 2$ in 2001.

[28] This is also true for P_1 and P_2 and significant at the 1% confidence level (results not shown). Consumption is higher in 2011 only for the extreme left tail of the distribution (Figure 1).

contrasts with multidimensional poverty estimates: money-metric measures show an *increase* in rural poverty over the period and a *non-significant change* in urban poverty.[29]

The increase in money-metric poverty contrasts with the improvement in standards of living observed in rural areas. Consequently, in rural areas, consumption has been more severely impacted by the adverse economic shock than long-term indicators such as education level, sanitation, etc. However, caution in making comparisons is warranted, because the money-metric poverty results may be influenced by the imprecise price deflator in the context of inflation and change of currency, and because the multidimensional poverty change between 2001 and 2011/12 is not fully robust when different variables are employed (see section 5).

Multidimensional and money-metric poor individuals are compared using a (money-metric) poverty line so that the same share of the population is poor under both poverty measures (corresponding to for $k = 2$ i.e. 69% in 2001 and 68% in 2011/12). The comparison shows that 78.5% of the multidimensional poor individuals are also money-metric poor (and vice versa) in 2001, and 79.9% in 2011/12 (Table A3). However the divergence between the measures is greater in urban areas. In 2001 only 60.5% (57.2% in 2011/12) of multidimensional poor individuals in urban areas are also money-metric poor, whereas 34.2% (43.7% in 2011/12) of the money-metric poor are also multidimensional poor. The difference is due to the much lower proportion of urban poor under the multidimensional measure (26.6% in 2001 and 28.3% in 2011/12) compared to the money-metric measure (47% in 2001 and 37% in 2011/12).

The profile of money-metric and multidimensional poor households also differs in some aspects (Table 8). Multidimensional poor have a higher average number of deprivations, a higher share of deprived individuals in each dimension, and a higher per capita consumption than money-

[29] Results available upon request. In urban areas, the *decrease* in poverty severity is significant at 5% level.

metric poor.[30] Money-metric poor live in larger households than multidimensional poor, but have similar characteristics in terms of household head gender, age, education and occupation. Differences in poverty profiles under the two measures suggest that money-metric poverty and multidimensional poverty are more dissimilar in urban areas and, thus, greater synergies may arise from complementary analysis.[31]

Finally, the results for M_0 are consistent with the MPI of Zimbabwe, based on the 2006 and 2010/11 DHS surveys (OPHI, 2013). The MPI has the equivalent of a weighted total of 10 possible deprivations and uses $k = 3.33$. It is composed of different variables than ours, categorized in three dimensions: education, health and living conditions. For 2010/11, the MPI analysis obtains $M_0 = 0.172$, $H = 0.391$ and $A = 0.440$ for $k = 3.33$, which compares to our result for 2011/12 of $M_0 = 0.192$, $H = 0.446$ and $A = 0.430$ for $k = 3$. The MPI also shows a decrease in M_0 between 2006 and 2010/2011 (ranging from -4.4% to -19.4% depending on the adjustments made) consistent with the decrease found between 2007 and 2011/12 of -11.4% for $k = 3$).[32]

5 Robustness checks

The first series of robustness tests consists of changing the dimensions and variables used to compute the A-F multidimensional poverty measure, the deprivation thresholds used, the weights for each variable, and the adjustments made to the A-F methodology (Table 9). These tests compute multidimensional poverty incidence M_0 for 2001, 2007 and 2011/12 and the changes

[30] These facts are expected by construction of the two poverty measures, since households with a high number of deprivations cannot be multidimensional non-poor, but households with high per capita consumption can be multidimensional poor.

[31] Multidimensional poverty indices can be used to target poor individuals as beneficiaries of social assistance programs (Alkire & Seth, 2013). Whether the index employed in this article would be appropriate for that purpose would depend on the objectives of the program and would require comparisons with other targeting methods.

[32] The MPI was only computed for 2006 and 2010/11 in Zimbabwe.

between periods (as in Table 3) for $k = 3$.[33] The 25 tests or variants of the multidimensional poverty measures confirm the robustness of the results between 2001 and 2007 (increase in poverty in all variants) and between 2007 and 2011/12 (decrease in poverty in all variants). The robustness tests also confirm the ambiguity of the overall change in poverty between 2001 and 2011/12. For most tests, the change is small (less than 10%) as in the main specification. However, poverty *decreases* or the change is not significant when health variables or water access are not included in the index. It also decreases when using equal or MCA/PCA weights, because these put more weight on living standards (assets, electricity, cooking fuel) which improved from 2001 to 2011/12. In contrast, poverty is found to increase by 13.4 to 15.8% when electricity, physical assets and rural variables are excluded from the measure or when lower thresholds (more restrictive definition of deprivation in each dimension) are employed.

The next robustness checks consist in using another multidimensional poverty index (from Bourguignon and Chakravarty, 2003) instead of the A-F measure (see Technical Appendix). The main difference between this Bourguignon and Chakravarty (B-C) index and the A-F index is that the B-C index does not use a counting threshold in computing the poverty measure. Instead, the B-C index takes into account deprivations of all households instead of censoring above a deprivation threshold k (which means taking into account only households with a certain number of deprivations). Results are similar to those of the A-F measure for $k = 1$ in terms of poverty levels and sign of change between each pair of periods, for $\propto = 0, 1, 2$ corresponding to the incidence, depth and severity of poverty (Table 7). This confirms the increase in poverty from 2001 and 2007 and the decrease in poverty between 2007 and 2011/12 in Zimbabwe. Also the B-

[33] The results are not shown for space purposes, but are available upon request. The use of PCA and MCA weights is described in the Technical Appendix.

C poverty index shows an insignificant difference between 2001 and 2011/12, confirming the ambiguity of the change during the overall period.

The last set of robustness checks adopts the fuzzy-set approach to multidimensional poverty to measure poverty changes in Zimbabwe (see Technical Appendix). Following equations (15)-(17), the TFA index is computed with two alternative sets of thresholds: the thresholds close to those used for the A-F and B-C indices, and the thresholds encompassing a wider range of values (indicated in Table A4). Regardless of the thresholds used, TFA results show that multidimensional poverty has increased from 2001 to 2007 and then decreased from 2007 to 2011/12 (Table 7). In this case the change from 2001 to 2011/12 is small but positive and significant.

6 Concluding remarks

This paper investigates the change in multidimensional poverty in Zimbabwe from 2001 to 2011/12 as the country plunged into acute crisis and then slowly recovered. Three datasets are used to study changes in well-being across dimensions such as education, health, living standards, access to services, before, during and after the peak of the crisis – the hyperinflation episode of 2008. The Alkire-Foster indices employed show that multidimensional poverty unambiguously increased in Zimbabwe from 2001 to 2007, and then decreased from 2007 to 2011/12 during the economic recovery. The results are robust to a wide range of alternative specifications. However, the overall change from 2001 to 2011 is ambiguous (i.e. not robust to alternative specifications) and not consistent across regions. In particular, multidimensional poverty increased from 2001 to 2011 in urban areas, where standards of living (such as access to electricity, cooking fuel, toilets, etc.) deteriorated during the crisis. But in rural areas, multidimensional poverty decreased from 2001 to 2011 overall.

Multidimensional well-being is fluid in times of crisis: long-term dimensions of well-being that are normally viewed as relatively fixed in the short to medium term changed rapidly in Zimbabwe. Further, changes in well-being vary across different dimensions, illustrating the need to aggregate deprivations in a meaningful index and to carefully examine the underlying components. Some dimensions appear to be resilient to the crisis, either remaining stable (access to toilets) or continuing long-term upward trends (educational attainment, access to electricity). Others deteriorated during the crisis and either recovered after 2007 (primary school enrollment, cooking fuel, access to services) or continued to worsen until 2011/12 (chronic illness, access to healthcare, clean source of water). Thus, the effect of the crisis is felt in the short-term through some dimensions and over the long-term in others.

These differences in changes in poverty dimensions during crisis and subsequent recovery also have implications for social assistance programs. While some dimensions require rapid delivery of social assistance to alleviate the immediate adverse effects of the crisis, others require long-term assistance program interventions to address lingering impacts on well-being. In particular, the experience from Zimbabwe demonstrates that social safety nets are needed in the short-term to avoid asset depletion and other harmful coping strategies, especially in the dimensions where households were hard-hit during the peak of the crisis in 2007: primary school enrollment (nationally), access to toilets, rural equipment and distance to services (in rural areas), and access to electricity, asset ownership and cooking fuel use (in urban areas). On the other hand, other dimensions require long-term support, often in the form of infrastructure repair and investment, since the deterioration continued after the peak of the crisis in health dimensions and access to clean water (nationally). Support for replenishment of household physical and human capital assets may also be needed as indicated by the long-term deterioration of livestock assets in rural areas and education levels in urban areas. Well-structured social assistance programs must, thus, address both the acute effect of the crisis when it happens and assist poor households recover from the crisis in the long-term, while building resilience to future shocks.

Technical appendix

A-F methodology

In the A-F methodology, the identification (step 1) is based on $g^{0'}$, a matrix of deprivations with a typical element $g_{ij}^{0'} = 1$ if an individual i is deprived in dimension j ($y_{ij} < z_j$) and $g_{ij}^{0'} = 0$ otherwise, so that a row vector $g_i^{0'}$ is an individual i's deprivation vector. A weight w_j is given to dimension j, so that we consider the weighted matrix g^0 where $g_{ij}^0 = w_j g_{ij}^{0'}$. This is used to create a vector c of weighted deprivations count, which is simply the weighted sum of individual i's deprivations: $c_i = \sum_j w_j g_{ij}^{0'} = \sum_j g_{ij}^0$. An individual is considered as multidimensionally poor if $c_i \geq k$, where $k \epsilon [1, d]$ is a poverty cutoff chosen to correspond to the union approach ($k = 1$), the intersection approach ($k = d$), or an intermediate approach when $k \epsilon (1, d)$. Using previous notations, this means that $\rho_k(y,z) = 1$ if $c_i \geq k$ and $\rho_k(y,z) = 0$ if $c_i < k$. Thus, the originality of the A-F index is to use a dual cutoff: a cutoff z_j for each deprivation, and a cutoff k for each individual. By combining both cutoffs, a censored deprivation matrix is generated: $g^0(k)$, where $g_{ij}^0(k) = g_{ij}^0$ for all j if $c_i \geq k$ and $g_{ij}^0(k) = 0$ for all j if $c_i < k$. Using this matrix to compute poverty measures allows us to take into account only deprivations of multidimensionally deprived individuals when computing the poverty index: in that way, we don't consider as poor an individual rich on every dimension but having a bad health, or not owning land in rural areas, etc., making the measure 'poverty focus'. We can also define $c(k)$, the censored vector of deprivations count, such that $c_i(k) = c_i * \rho_k(y_i, z)$: it takes as a value the number of deprivations if the individual is poor, and 0 otherwise.

When variables are cardinal, one can go beyond g^0 and construct g^1 such that $g_{ij}^1 = g_{ij}^0(z_j - y_j)/z_j$. Then, $g^{\propto}$ can be constructed by raising g^1 to the power $\propto$ so that

$g_{ij}^{\propto} = (g_{ij}^{1})^{\propto}$. Similarly to $g^0(k)$, we can create $g^{\propto}(k)$, with $g_{ij}^{\propto}(k) = \rho_k(y,z) * g_{ij}^{\propto}$ so that a row $g_i^{\propto}(k)$ consists of 0 elements for all j if $c_i < k$.

These identification methods based on $g^{\propto}$ and ρ_k lead to natural multidimensional poverty measures (step 2). H is the headcount ratio, A the average deprivation share among the poor, and M a multidimensional poverty measure combining them:

$$H = H_k(y,z,) = \frac{1}{n}\sum_{i}^{n} \rho_k(y,z) = \frac{q}{n} \tag{6}$$

where $q = \sum_{i}^{n} \rho_k(y,z)$ or the number of poor

$$A = \frac{|c(k)|}{qd} \tag{7}$$

where $d = \sum_{j} w_j$ or the maximum level of deprivation

$$M_0 = HA = \mu\big(g^0(k)\big) = \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{g_{ij}^0}{nd} \tag{8}$$

M_0, our main measure of multidimensional poverty, is the adjusted headcount ratio, which combines the ratio of poor in the population and their level of deprivation: it is weighted sum of the deprivations among all the poor, divided by the population size and the maximum number of deprivations (i.e. the weighted total of dimensions considered). It is sensitive to the incidence of poverty and to its breadth, measured as the number of deprivations.

However, M_0 does not reflect the depth of deprivation inside each dimension. For instance, as long as an individual is above the deprivation threshold z in assets, poverty measured by M_0 is not sensitive to a worsening of this individual’s situation if it loses some of its meager assets. For that reason, it is important to consider a FGT class of A-F multidimensional poverty measures:

$$M_{\propto} = \mu\left(g^{\propto}(k)\right) \text{ for } \propto \geq 0 \tag{9}$$

In particular, the adjusted poverty gap is given by:

$$M_1 = \mu\left(g^1(k)\right) = HAG \tag{10}$$

where $G = |g^1(k)|/|g^0(k)|$ or the average poverty gap in all dimensions in which poor individuals are deprived. This measure is sensitive to the intra-dimensional depth of poverty. Similarly, the adjusted poverty severity is given by:

$$M_2 = \mu\left(g^2(k)\right) = HAS \tag{11}$$

where $S = |g^2(k)|/|g^0(k)|$ or the average poverty severity in all dimensions in which poor individuals are deprived. This measure is sensitive to the inequality in the distribution of deprivations among the poor.

Note that $M_{\propto}$ can also be decomposed by individual (or group) and by dimension. When the population n is decomposed into m subgroups such that $n = \sum_1^m n^l$:

$$M_{\propto} = \frac{\sum_i \mu\left(g_i^{\alpha}(k)\right)}{n} = \sum_1^m \frac{n^l}{n} M_{\propto}(y^l; z) \tag{12}$$

$$M_{\propto} = \sum_j \mu(g_{*j}^{\alpha}(k)) / d \tag{13}$$

Equation (12) shows that $M_{\propto}$, the overall poverty in the population, is the average of the individual poverty levels, and is decomposable by subgroups. Equation (13) shows that after identification has been done, we can consider $M_{\propto}$ as a weighted average of dimensional values, and $\frac{\mu(g_{*j}^{\alpha}(k))/d}{M_{\propto}}$ as the contribution share of dimension j to $M_{\propto}$.

Bourguignon and Chakravarty indices and Fuzzy Set approach to multidimensional poverty

The literature contains several other functional forms for multidimensional indices. Among others, Bourguignon and Chakravarty (2003) propose a multidimensional generalization of the FGT poverty index:

$$P_{\propto} = \frac{1}{n}\sum_{j=1}^{m}\sum_{i \in N} w_j * b_{ij} * (1 - \frac{y_{ij}}{z_j})^{\propto} \quad (14)$$

where $w_j > 0$ is a weight attributed to dimension j, $\propto \geq 0$ and $b_{ij} = \begin{cases} 1 \text{ if } y_{ij} < z_j \\ 0 \text{ otherwise} \end{cases}$. For $\propto = 0$, this measure is simply the weighted aggregation of deprivations over all individuals. This index satisfies several desirable properties, including monotonicity, poverty focus, continuity and decomposability.

Another branch of the multidimensional poverty literature has taken advantage of the mathematical concept of fuzzy-sets (Zadeh, 1965). This approach has a particular philosophical stakes at poverty, which is considered as "fuzzy" and relative (Qizilbash, 2006). However, it has strong theoretical links with other axiomatic approaches (Chakravarty, 2006). In practice, the fuzzy-set approach has often been used as a complement or a robustness test of other multidimensional poverty measures described above (Deutsch and Silber, 2005). A fuzzy set A is characterized by a membership function $\mu_A(x) \in [0,1]$ which indicate the degree of membership of x to the fuzzy set A, with $\mu_A(x) = 0$ indicating that x does not belong to A, $\mu_A(x) = 1$ that x totally belongs to A, and $0 < \mu_A(x) < 1$ that x only partially belongs to A. This theory was applied in the analysis of poverty for the first time in 1990 by Cerioli and Zani. The authors define a "Totally Fuzzy Approach" (TFA) where the degree of deprivation μ_A in a given dimension j depends, for a continuous variable x, on: i) threshold x_{min} below which an individual is clearly poor; ii) a threshold x_{max} above which an individual is clearly not poor; iii) an area between x_{min} and x_{max} where this poverty condition of the individual is unclear, or the degree of deprivation is only partial. $\mu_A(x_{ij})$ is defined as such:

$$\mu_A(x_{ij}) = 1 \text{ if } x_{ij} \leq x_{jmin}$$

$$\mu_A(x_{ij}) = 0 \text{ if } x_{ij} \geq x_{jmax} \tag{15}$$

$$\mu_A(x_{ij}) = \frac{x_{jmax} - x_{ij}}{x_{jmax} - x_{jmin}} \text{ if } x_{jmin} < x_{ij} < x_{jmax}$$

And for dichotomous variables:

$$\mu_A(x_{ij}) = 1 \text{ if } x_{ij} = 0 \tag{16}$$

$$\mu_A(x_{ij}) = 0 \text{ if } x_{ij} = 1$$

The poverty measure is the weighted aggregation of levels of deprivations across m dimensions:

$$P_{TFA} = \frac{\sum_i^n \sum_j^m \mu_A(x_{ij})}{n \sum_j^m w_j} \tag{17}$$

with w_j being the weight assigned to dimension j.[34]

The TFA is mathematically similar to the A-F approach when M_1 is used, with two notable differences: similarly to the B-C measure, deprivations are aggregated among all households, not only those above a counting threshold; and there is a x_{jmin} threshold below which an individual is considered fully deprived in dimension j.

Modifications of the A-F methodology

In the A-F methodology, households for which a value is missing for at least one dimension is not included in the computation of the index. In addition, missing values at the *individual* level

[34] This approach has been extended by Cheli & Lemmi (1995) who defined a Totally Fuzzy and Relative (TFR) approach based on the *distribution* of achievements. However, the TFR is less suited to make inter-temporal comparisons, which is our purpose in this paper.

have to be managed without discarding too many information, for variables based on individual modules rather than household modules. The approach followed is inspired by the MPI index methodology (Table A5) (Alkire and Santos, 2011).

Another methodological issue is the fact that given the A-F methodology, larger households tend to be considered as having more deprivations than smaller households because the probability of being deprived in education, health and employment increases mechanically with the number of household members. Because larger households are often found to be poorer *de facto* in Sub-Saharan Africa, it is desirable to avoid adding this *mechanical* effect. For this reason, the *weight* of the deprivation is corrected to take into account household size. In generating this adjusted weight, the number of individuals deprived (not attending school, unemployed, etc.) is also taken into account when possible, so that larger households with many deprived individuals are not mechanically advantaged either by the weighting system (Table A5). The general adjusted (weighted) element of the deprivation vector $g^0_{ij,adj}$ for household i is:

$$g^0_{ij,adj} = aw_i * g^0_{ij}$$

where aw_i is the adjusted weight and g^0_{ij} is an element of the deprivation vector g^0_i. These adjusted deprivation vectors $g^0_{i,adj}$ are used in the computation of M_α. This constitutes a modest contribution to the A-F methodology. Also, results are robust to the use of not-adjusted weights.

In the creation of the variables, an effort was made to obtain cardinal variables rather than dichotomous variables (even when the original variable is ordinal), in order to obtain a richer $g^\propto$ matrix (when $\propto > 0$) not made only of 0 and 1 but capturing the gap from the threshold (Table A6). This allows us to generate M_1 and M_2 multidimensional poverty measures, which is usually not done in empirical applications (the MPI for instance includes only M_0).

Finally, because several of our deprivation variables are dichotomous (0/1), the weights in the g_1 and g_2 matrices had to be adjusted so that these dichotomous variables do not mechanically weight more. The issue is that for an household deprived in level of education and chronic health, the weight is 1 in g_0. But $g_{ij}^1 = (z_j - y_j)/z_j$, so $g_{i,educmax}^1 \leq 1$ (and will likely be strictly less than 1 on average) while we always have $g_{i,healthchronic}^1 = 1$. For this reason, weights were modified in order to keep the original importance of deprivations, while keeping the same weighted sum of deprivations in urban and rural areas (Table A7). Results are robust to the use of the g_0 weights for g_1 and g_2.

Construction of the money-metric poverty measure

The construction of money-metric poverty measure presents the challenge of using an appropriate deflator for variations of price across regions and over time. The choice of the right price deflator is even more crucial in our case because we are considering two different datasets with 10 years between them. To construct this price deflator, price data collected monthly by ZIMSTAT on a basket of 18 items are used. Ideally, we would have liked to adopt a money metric utility approach to construct consumption aggregates and use Paasche indices as deflators (Deaton and Zaidi, 2002), but the prices data were only available for the 18 items used by ZIMSTAT to construct the poverty datum line (ZIMSTAT, 2013, Annex D). Consequently, a welfare ratio approach is adopted to construct our price deflator (Deaton and Zaidi, 2002; Ravallion, 1998) and weights computed by ZIMSTAT are used to represent the cost of consumption of the minimum food needs (see Table A8 for the basket used to construct the price deflator). Poverty lines were used as price deflators for variations in space and time, which is a common practice (Dercon and Krishnan, 1998). The price data come from ZIMSTAT which collects monthly local price data.

According to Deaton and Zaidi (2002), followed in this analysis, there is much debate about the way to properly measure aggregate consumption/expenditures, especially regarding lumpy or difficult-to-measure expenditures. It was not possible to derive consumption flows from durable assets, for which there is no information regarding their value or their age in the ICES/PICES datasets. Because the ICES/PICES questionnaires record expenditures occurring during the last month, including lumpy expenditures will mechanically make households non-poor if they have a major expense (wedding, school fees, purchase of expensive durable) occurring this particular month. However, it was possible to spread over 12 months expenditures on education, and over 12 months (cellphones, etc.), 60 months (bikes, etc.) or 120 months (cars, etc.) expenditures on durables. Expenditures on health care and ceremonies were excluded, as well as expenditures on rent or the rent imputed value, given the fact that most households do not pay rent (especially in rural areas). Results are robust to alternative computations of the consumption aggregate: excluding education and durables; including all expenditures; including all expenditures except rent; excluding households below the 1^{st} expenditures percentile and above the 99^{th} expenditures percentiles; or using alternative adult equivalent scales to compute per capita expenditures.

Use of PCA and MCA weights

Multidimensional poverty analyses have often resorted to Principal Component Analysis (PCA) (Klasen, 2000; Roche, 2008) or Multiple Correspondence Analysis (MCA) (Asselin, 2002; Batana and Duclos, 2008; Ezzrari and Verme, 2012; Njong and Ningaye, 2008; Wardhana, 2010) as ways to set up weights or construct a composite indicator. There are drawbacks to this "statistical" way of setting weights, mentioned by these authors and others (Decancq and Lugo, 2008).[35] Nevertheless, these technics are employed as robustness tests in this paper. When using PCA, factor loading of each variable are used as weight; for MCA, the difference between the weight associated between being deprived in dimension j $(g_j^o = 1)$ and the weight associated with not being deprived in dimension j $(g_j^o = 0)$ are used. Only variables present in both urban and rural areas are included in order to avoid capturing other geographical factors. For $k = 3$, multidimensional poverty indices M_0 obtained are higher, because PCA and MCA give more weights to attributes from which many households are deprived (such as physical assets, cooking fuel, etc.) rather than less common deprivations (such as education ones).

[35] These drawbacks include: emphasis on correlation between dimensions, lack of transparency, interpretation, possibly normatively inappropriate results, non-accordance with people's perceptions, etc. An additional issue in our case is the choice of year to run the PCA and MCA.

References

Alkire, S. (2007). Choosing dimensions: The capability approach and multidimensional poverty. *Chronic Poverty Research Centre Working Paper*(88).

Alkire, S., and Foster, J. (2011a). Counting and multidimensional poverty measurement. *Journal of Public Economics* no. 95 (7):476-487.

Alkire, S., and Foster, J. (2011b). Understandings and misunderstandings of multidimensional poverty measurement. *The Journal of Economic Inequality* no. 9 (2):289-314.

Alkire, S., and Santos, M. E. (2011). Acute multidimensional poverty: a new index for developing countries.

Alkire, S., and Seth, S. (2013). Selecting a targeting method to identify BPL households in India. Social indicators research, 112(2), 417-446.

Alwang, J., Mills, B. F., and Taruvinga, N. (2002a). Changes in Well-being in Zimbabwe, 1990-6: Evidence Using Semi-parametric Density Estimates. *Journal of African Economies* no. 11 (3):326-364.

Alwang, J., Mills, B. F., and Taruvinga, N. (2002b). *Why has poverty increased in Zimbabwe?* : World Bank Publications.

AMCOW. (2010). Water Supply and Sanitation in Zimbabwe: Turning Finance into Services for 2015 and Beyond *An AMCOW Country Status Overview*.

Asselin, L.-M. (2002). Composite indicator of multidimensional poverty. *Multidimensional Poverty Theory*.

Atkinson, T. (2003). Multidimensional deprivation: contrasting social welfare and counting approaches. *The Journal of Economic Inequality* no. 1 (1):51-65.

Atkinson, T., Cantillon, B., Marlier, E., and Nolan, B. (2002). *Social indicators: The EU and social inclusion*: Oxford University Press on Demand.

Batana, Y. M., and Duclos, J.-Y. (2008). Multidimensional poverty dominance: statistical inference and an application to west Africa. *Cahier de recherche/Working Paper*, *8*, 08.

Besada, H., and LaChapelle, J. (2011). Zimbabwe's recovery path: a conceptual framework. In H. Besada (Ed.), *Zimbabwe: picking up the pieces*.

Bird, K., and Shepherd, A. (2003). Livelihoods and chronic poverty in semi-arid Zimbabwe. *World Development* no. 31 (3):591-610.

Boadi, K. O., and Kuitunen, M. (2006). Factors affecting the choice of cooking fuel, cooking place and respiratory health in the Accra metropolitan area, Ghana. *Journal of biosocial Science* no. 38 (3):403.

Booysen, F., Van Der Berg, S., Burger, R., Maltitz, M. v., and Rand, G. d. (2008). Using an asset index to assess trends in poverty in seven Sub-Saharan African countries. *World Development* no. 36(6):1113-1130.

Bossert, W., Chakravarty, S. R., and D'Ambrosio, C. (2009). Multidimensional poverty and material deprivation.

Bossert, W., Chakravarty, S. R., and D'Ambrosio, C. (2012). Multidimensional poverty and material deprivation with discrete data. *Review of income and wealth*.

Bourguignon, F., and Chakravarty, S. R. (2003). The measurement of multidimensional poverty. *The Journal of Economic Inequality* no. 1 (1):25-49.

Cerioli, A., and Zani, S. (1990). A fuzzy approach to the measurement of poverty *Income and wealth distribution, inequality and poverty* (pp. 272-284): Springer.

Chakravarty, S. R. (2006). An axiomatic approach to multidimensional poverty measurement via fuzzy sets. In A. Lemmi and G. Betti (Eds.), *Fuzzy set approach to multidimensional poverty measurement* (pp. 49-72): Springer.

Cheli, B., and Lemmi, A. (1995). A" Totally" fuzzy and relative approach to the multidimensional analysis of poverty. *ECONOMIC NOTES-SIENA-*, 115-134.

CMEPSP, Stiglitz, J. E., Sen, A., and Fitoussi, J.-P. (2009). Report by the commission on the measurement of economic performance and social progress.

CSO. (1998). *Poverty in Zimbabwe*. Harare, Zimbabwe.

Datt, G. (2013). Making every dimension count: multidimensional poverty without the “dual cut off”.

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

Decancq, K., and Lugo, M. A. (2008). Setting weights in multidimensional indices of well-being: Working Paper, Department of Economics, University of Oxford.

Dercon, S., and Krishnan, P. (1998). *Changes in poverty in rural Ethiopia 1989-1995: measurement, robustness tests and decomposition*: Centre for the Study of African Economies, Institute of Economics and Statistics, University of Oxford.

Deutsch, J., and Silber, J. (2005). Measuring multidimensional poverty: An empirical comparison of various approaches. *Review of income and wealth* no. 51 (1):145-174.

Duclos, J.-Y., Sahn, D., and Younger, S. D. (2006a). Robust multidimensional poverty comparisons. *The Economic Journal* no. 116 (514):943-968.

Duclos, J.-Y., Sahn, D., and Younger, S. D. (2006b). Robust multidimensional spatial poverty comparisons in Ghana, Madagascar, and Uganda. *The World Bank Economic Review* no. 20 (1):91-113.

Ellegård, A. (1996). Cooking fuel smoke and respiratory symptoms among women in low-income areas in Maputo. *Environmental Health Perspectives* no. 104 (9):980.

Ersado, L., Alderman, H., and Alwang, J. (2003). Changes in Consumption and Saving Behavior before and after Economic Shocks: Evidence from Zimbabwe. *Economic Development and Cultural Change* no. 52 (1):187-215.

Ezzrari, A., and Verme, P. (2012). A multiple correspondence analysis approach to the measurement of multidimensional poverty in Morocco, 2001-2007. *World Bank Policy Research Working Paper*(6087).

Ferreira, F., and Lugo, M. A. (2012). Multidimensional poverty analysis: Looking for a middle ground. *World Bank Policy Research Working Paper*(5964).

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

Gallo, C. R., and Roche, J. M. (2013). *The dimensions of poverty in Venezuela and changes over time between 1997 and 2010: a proposal of a multidimensional poverty measure*.

Garcia, S., and Ritterbush, A. (2013). Child poverty in Colombia: construction of a multidimensional measure using a mixedmethods approach.

Gordon, D., Nandy, S., Pantazis, C., Pemberton, S., and Townsend, P. (2004). The distribution of child poverty in the developing world. *Report to UNICEF, Centre for International Poverty Research, Bristol University, UK*.

Hamdok, A. A. (1999). A poverty assessment exercise in Zimbabwe. *African Development Review* no. 11 (2):290-306.

Hanke, S. H. (2008, December 22). The Printing Press. *Forbes Magazine*.

Hanke, S. H. (2012). Zimbabwe: From hyperinflation to growth.
Hanke, S. H., and Kwok, A. K. (2009). On the measurement of Zimbabwe's Hyperinflation. *Cato J.*, *29*, 353.
Hoddinott, J., and Kinsey, B. (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics* no. 63 (4):409-436.
Klasen, S. (2000). Measuring poverty and deprivation in South Africa. *Review of income and wealth* no. 46 (1):33-58.
Laderchi, C. R., Saith, R., and Stewart, F. (2003). Does it matter that we do not agree on the definition of poverty? A comparison of four approaches. *Oxford Development Studies* no. 31 (3):243-274.
Larochelle, C., Alwang, J., and Taruvinga, N. (2014). Inter-temporal Changes in Well-being During Conditions of Hyperinflation: Evidence from Zimbabwe. *Journal of African Economies*, ejt028.
Larochelle, C., and Alwang, J. R. (2012). Schooling achievement amongst Zimbabwean children during a period of economic chaos, 2001-2007/8.
Mack, J., and Lansley, S. (1985). *Poor Britain*: G. Allen and Unwin.
Makochekanwa, A., and Kambarami, P. (2011). Zimbabwe's hyperinflation: can dollarization be the cure? In H. Besada (Ed.), *Zimbabwe: picking up the pieces* (pp. 107-128).
Makochekanwa, A., and Kwaramba, M. (2010). Dwindling access to basic services in Zimbabwe.
Marquette, C. M. (1997). Current poverty, structural adjustment, and drought in Zimbabwe. *World Development* no. 25 (7):1141-1149.
Mashakada, T. L. J. (2013). *Macroeconomic consequences of fiscal deficits in developing countries: a comparative study of Zimbabwe and selected African countries (1980-2008).* Stellenbosch: Stellenbosch University.
Moyo, S. (2011). Three decades of agrarian reform in Zimbabwe. *Journal of Peasant Studies* no. 38 (3):493-531.
Mpofu, B. (2011). Some Perceptions on the Poverty Question in Zimbabwe. *Solidarity Peace Trust, http://www. solidaritypeacetrust. org/1109/some-perceptions-on-the-poverty-question-in-zimbabwe/(Accessed 16 th August 2012)*.
Murithi, T., and Mawadza, A. (2011). *Zimbabwe in Transition: A View from Within*: Jacana Media.
Mushongah, J. (2009). *Rethinking Vulnerability: Livelihood Change in Southern Zimbabwe, 1986-2006.* University of Sussex.
Ndlela, T. (2011). Evolution of Zimbabwe’s economic tragedy: a chronological review of macroeconomic policies and transition to the economic crisis.
Njong, A. M., and Ningaye, P. (2008). Characterizing weights in the measurement of multidimensional poverty: An application of data-driven approaches to Cameroonian data. *Retrieved from Oxford Poverty and Human Development Initiative (OPHI) website: http://www. ophi. org. uk/wp-content/uploads/OPHI-wp21. pdf*.
NMottsConsulting. (2004). Zimbabwe: Case Study of the Workability of Fortification via Service Hammer Mills *The Micronutrient Initiative*.
Nyazema, N. Z. (2010). The zimbabwe crisis and the provision of social services health and education. *Journal of Developing Societies* no. 26 (2):233-261.
OPHI. (2013). Country Briefing: Zimbabwe. In O. C. B. 2013 (Ed.), *Multidimensional Poverty Index (MPI) At a Glance*. Oxford, United Kingdom.

Potts, D. (2006). ‘All my hopes and dreams are shattered’: Urbanization and migrancy in an imploding African economy–the case of Zimbabwe. *Geoforum* no. 37 (4):536-551.

Potts, D. (2009). The slowing of sub-Saharan Africa's urbanization: evidence and implications for urban livelihoods. Environment and Urbanization no. 21 (1):253-259.

Potts, D., and Mutambirwa, C. (1998). “Basics are now a luxury”: perceptions of structural adjustment's impact on rural and urban areas in Zimbabwe. *Environment and Urbanization* no. 10 (1):55-76.

Qizilbash, M. (2006). Philosophical accounts of vagueness, fuzzy poverty measures and multidimensionality. In A. Lemmi and G. Betti (Eds.), *Fuzzy Set Approach to Multidimensional Poverty Measurement*: Springer.

Ravallion, M. (1998). *Poverty lines in theory and practice*: World Bank Publications.

Ravallion, M. (2011). On multidimensional indices of poverty. *Journal of Economic Inequality*.

Reddy, S., and Pogge, T. (2009). How not to count the poor.

Reddy, S., Visaria, S., and Asali, M. (2006). Inter-country comparisons of poverty based on a capability approach: an empirical exercise. United Nations Development Programme International Poverty Center Working Paper(27).

Rehfuess, E., Mehta, S., and Prüss-Üstün, A. (2006). Assessing household solid fuel use: multiple implications for the Millennium Development Goals. *Environmental Health Perspectives* no. 114 (3):373.

Richardson, C. (2013). Zimbabwe: Why is One of the World's Least-Free Economies Growing so Fast? *Cato Institute Policy Analysis*(722).

Robertson, J. (2011). A macroeconomic policy framework for economic stabilisation in Zimbabwe. In H. Besada (Ed.), *Zimbabwe: picking up the pieces*.

Robeyns, I. (2005). Selecting capabilities for quality of life measurement. *Social indicators research* no. 74 (1):191-215.

Roche, J. M. (2008). Monitoring Inequality among Social Groups: A Methodology Combining Fuzzy Set Theory and Principal Component Analysis. *Journal of Human Development* no. 9 (3):427-452.

Scoones, I., Marongwe, N., Mavedzenge, B., Mahenehene, J., Murimbarimba, F., and Sukume, C. (2010). *Zimbabwe's land reform: myths and realities*: James Currey Oxford.

Scoones, I., Marongwe, N., Mavedzenge, B., Murimbarimba, F., Mahenehene, J., and Sukume, C. (2012). Livelihoods after land reform in Zimbabwe: understanding processes of rural differentiation. *Journal of Agrarian Change* no. 12 (4):503-527.

Sen, A. (1985). Well-being, agency and freedom: the Dewey lectures 1984. *The Journal of Philosophy* no. 82 (4):169-221.

Sen, A. (1993). Capability and well-being. In M. Nussbaum and A. Sen (Eds.), *The quality of life* (pp. 30–53). Oxford,: Clarendon Press.

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

Shamu, S. (2012). *Resource mobilisation for health under the Zimbabwe Investment Case*. EQUINET Discussion Paper Series 94. Training and Research Support Centre, EQUINET. Harare.

Tsui, K.-y. (2002). Multidimensional poverty indices. *Social Choice and Welfare* no. 19 (1):69-93.

UNZ. (2012). ZIMBABWE 2012 Millennium Development Goals Progress Report.

Vranken, J. (2002). *Belgian reports on poverty*. Paper presented at the conference “Reporting on Income Distribution and Poverty–Perspectives from a German and an European Point of View” organized by the Hans Böckler Stiftung, Berlin.

Wardhana, D. (2010). Multidimensional Poverty Dynamics in Indonesia (1993-2007). *University of Nottingham: School of Economics*.

Watts, H., Gregson, S., Saito, S., Lopman, B., Beasley, M., and Monasch, R. (2007). Poorer health and nutritional outcomes in orphans and vulnerable young children not explained by greater exposure to extreme poverty in Zimbabwe. *Tropical medicine and international health* no. 12 (5):584-593.

Yalonetzky, G. (2011). A Note on the Standard Errors of the Members of the Alkire Foster Family and its Components. *OPHI Research in Progress, 25*.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control* no. 8 (3):338-353.

ZIMSTAT. (2013). Poverty and Poverty Datum Line Analysis in Zimbabwe 2011/12. Harare, Zimbabwe.

Tables

Table 1: Dimensions, variables and weights for the A-F multidimensional poverty indices

Dimension	Dimension weight	Variable	Variable weight urban	Variable weight rural
Education	**2**	Nobody in the household completed primary school	1	1
		The household has one child between 6 and 12 not enrolled in school	1	1
Health	**2**	One member of the household is chronically ill	1	1
		One member of the household has been ill but did not get health care in the previous 30 days	1	1
Employment	**1 urban**	One member of the household was unemployed as main occupation in the last 12 months	1	-
Housing conditions	**1 rural 1.5 urban**	The house does not have electricity	1	0.5
		The house does not have toilets (pit, Blair or flush toilets) in rural areas or flush toilets in urban areas	0.5	0.5
Living conditions	**1**	The source of water is an unprotected well (or worse) or is located farther than 1 km away in rural areas; the source of water is not piped water on premise in urban areas	0.5	0.5
		The household cooks with wood	0.5	0.5
Assets	**1**	The asset index of the household is below a given threshold	1	1
Agricultural assets	**1.5 rural**	The household has less than 0.25 hectares of land	-	0.5
		The animal index of the household is below a given threshold (<1 TLU)	-	0.5
		The household has no agricultural equipment	-	0.5
Access to services	**1**	The household is far from 2 essential services or more	1	1

Table 2: Raw headcount ratios for the indicators used in 2001, 2007 and 2011/12

Year	2001			2007			2011/12		
	All	Rural	Urban	**All**	Rural	Urban	**All**	Rural	Urban
No one with 7 or more years of education	**0.091**	0.122	0.020	**0.063***	0.081*	0.015	**0.058‡**	0.067**	0.031**
Child not in school	**0.037**	0.048	0.013	**0.049***	0.061*	0.016	**0.025****	0.028**	0.017
Chronically ill	**0.093**	0.092	0.096	**0.139***	0.151*	0.105	**0.163****	0.183**	0.107
Did not get health care	**0.045**	0.042	0.051	**0.069***	0.078*	0.046	**0.111****	0.119**	0.089**
Unemployed	-	-	**0.275**	-	-	**0.255**	-	-	**0.260**
No electricity	**0.653**	0.896	0.106	**0.636***	0.812*	0.159*	**0.486****	0.619**	0.115*
No toilets	**0.316**	0.441	0.036	**0.321**	0.411*	0.076*	**0.314**	0.388**	0.108**
Unprotected water	**0.228**	0.312	0.039	**0.288***	0.366*	0.079*	**0.362****	0.405**	0.244**
Wood as cooking fuel	**0.720**	0.972	0.154	**0.731**	0.910*	0.248*	**0.715***	0.900‡	0.200**
Low asset index	**0.602**	0.719	0.340	**0.600**	0.718	0.283*	**0.557****	0.661**	0.267‡
Small land	-	**0.145**	-	-	**0.156**	-	-	**0.133****	-
Low TLU	-	**0.371**	-	-	**0.411***	-	-	**0.451****	-
Low rural equipment	-	**0.293**	-	-	**0.335***	-	-	**0.309****	-
Far from services	**0.285**	0.367	0.101	**0.390***	0.494*	0.109	**0.288***	0.362*	0.081**
Observations	19790	12526	7264	13049	10847	2202	28935	23920	5015

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. Headcounts ratios are the share of individuals deprived in each variable weighted using survey weights for observations without missing values (see Technical Appendix). Sample weights are applied to household observations to obtain nationally representative figures at the individual level.
* Significantly different (at 5%) from the previous period (Wald test).
** Significantly different (at 5%) from the two previous periods (Wald test).
‡ Significantly different from the first period only, for 2011 (Wald test).

Table 3: A-F poverty multidimensional indices M_0, M_1 and M_2, and percentage change

M_0						
k	2001	2007	2011/12	% change 2001-2007	% change 2007-2011/12	% change 2001-2011/12
1	0.264	0.290	0.275	9.8*	-5.1*	4.2*
2	0.241	0.268	0.249	11.0*	-7.1*	3.1*
3	0.180	0.216	0.192	20.1*	-11.4*	6.4*
4	0.097	0.130	0.109	34.1*	-16.5*	12.0*
M_1						
k	2001	2007	2011/12	% change 2001-2007	% change 2007-2011/12	% change 2001-2011/12
1	0.158	0.179	0.165	13.1*	-7.7*	4.5*
2	0.145	0.165	0.149	13.5*	-9.6*	2.6*
3	0.110	0.134	0.115	21.6*	-14.2*	4.4*
4	0.060	0.081	0.065	34.1*	-20.2*	7.0*
M_2						
k	2001	2007	2011/12	% change 2001-2007	% change 2007-2011/12	% change 2001-2011/12
1	0.131	0.150	0.137	14.5*	-8.4*	4.9*
2	0.119	0.137	0.123	14.6*	-10.1*	3.0*
3	0.090	0.110	0.095	22.7*	-14.3*	5.2*
4	0.049	0.067	0.053	35.3*	-19.9*	8.5*

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. See text and Technical Appendix for detail of the computation of M_α. Percentage changes are computed as $100 * (M_{\alpha,t} - M_{\alpha,t-a})/M_{\alpha,t-a}$. Sample weights are applied to household observations to obtain nationally representative figures at the individual level. Stars indicate significance of the changes at 5%, computed following Yalonetzky (2011).

Table 4: Headcount ratio (H) and Average deprivation share (A) in the A-F indices

H	2001	2007	2011/12	Change 2001-2007	Change 2007-2011	Change 2001-2011
k=1	0.861	0.874	0.867	0.013*	-0.007	0.006
k=2	0.685	0.710	0.677	0.025**	-0.033**	-0.008
k=3	0.434	0.501	0.446	0.067**	-0.055**	0.012
k=4	0.196	0.256	0.209	0.060**	-0.047**	0.013**
A	2001	2007	2011/12	Change 2001-2007	Change 2007-2011	Change 2001-2011
k=1	0.307	0.332	0.317	0.025**	-0.014**	0.011**
k=2	0.352	0.377	0.367	0.025**	-0.010**	0.015**
k=3	0.415	0.432	0.430	0.016**	-0.002	0.014**
k=4	0.497	0.509	0.521	0.012**	0.012**	0.024**

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. See text for detail of the computation. Sample weights are applied to household observations to obtain nationally representative figures at the individual level. Changes are percentage point differences between the pairs of years.

* Significant at 5% (Wald test).

** Significant at 1% (Wald test).

Table 5: Percentage contribution of each dimension to the A-F multidimensional poverty indices M_α for k=3

	M_0			M_1			M_2		
	2001	2007	2011/12	2001	2007	2011/12	2001	2007	2011/12
Below 7 years of education	3.6	2.3	2.2	3.2	1.9	1.6	2.1	1.2	0.8
Child does not go to school	1.5	1.8	1.0	2.9	3.5	1.8	3.1	3.7	1.8
Chronic illness	4.3	**6.2**	**8.6**	3.5	**5.0**	**7.2**	4.3	**6.1**	**8.8**
No health visit	2.9	4.3	**7.7**	2.4	3.4	**6.4**	2.9	4.2	**7.8**
Unemployed	2.3	1.5	1.3	2.8	1.8	1.7	3.5	2.2	2.0
Low assets	**22.7**	**22.0**	**21.1**	**29.4**	**30.1**	**28.1**	**31.2**	**33.1**	**29.7**
Far from services	**12.6**	**15.2**	**12.0**	**11.2**	**13.6**	**10.0**	**6.7**	**8.0**	**5.3**
No electricity	**12.1**	**11.7**	**10.0**	**6.8**	**6.6**	**5.8**	**8.3**	**8.0**	**7.0**
Wood as cooking fuel	**12.2**	**11.9**	**11.6**	**10.0**	**9.6**	**9.7**	**12.2**	**11.6**	**11.8**
Unprotected water source	**5.1**	**5.7**	**6.7**	**6.4**	**6.9**	**8.7**	4.7	**5.0**	**6.7**
No toilet	**7.1**	**6.7**	**6.5**	**5.9**	**5.8**	**5.7**	3.7	4.0	3.7
Small land	2.3	1.3	1.2	4.0	2.3	1.9	4.7	2.7	2.1
Low TLU	**6.1**	**5.2**	**6.0**	**9.0**	**7.5**	**9.4**	**9.6**	**7.8**	**10.1**
Rural equipment	**5.1**	4.3	4.1	2.5	2.1	2.1	3.1	2.6	2.5
TOTAL	***100***	***100***	***100***	***100***	***100***	***100***	***100***	***100***	***100***

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. Percentage contributions are computed following equation (13) as $\frac{\mu(g^{\alpha}_{*j}(k))/d}{M_\alpha}$ (see Technical Appendix). Sample weights are applied to household observations to obtain nationally representative figures at the individual level. Bold indicates percentages higher than 5%.

Table 6: FGT money-metric poverty indices in 2001 and 2011/12

	Estimate	Std. Err.	[99% Conf.	Interval]
2001				
p0	0.685	0.005	0.673	0.697
p1	0.323	0.003	0.315	0.331
p2	0.189	0.002	0.183	0.195
2011				
p0	0.748	0.004	0.737	0.758
p1	0.385	0.003	0.378	0.392
p2	0.238	0.002	0.232	0.243
Change				
p0 change	6.3*	**p0 % change**	9.6*	
p1 change	6.2*	**P1 % change**	20.1*	
p2 change	4.9*	**P2 % change**	26.9*	

***Source*: our calculations with 2001 and 2011/12 ICES/PICES data. See text for detail of the computation. Percentage changes are computed as $(P_{\propto,t} - P_{\propto,t-a})/P_{\propto,t-a}$. Sample weights are applied to household observations to obtain nationally representative figures at the individual level.**

*** Significant at 1% level.**

Table 7: Robustness tests: Bourguignon- Chakravarty (B-c) and Totally Fuzzy Approach (TFA) multidimensional poverty measures

B-C measure	*2001*	*2007*	*2011/12*	*% Change 2001-2007*	*% Change 2007-2011/12*	*% Change 2001-2011/12*
P0	0.292	0.325	0.296	11.3*	-8.8*	1.4
P1	0.232	0.262	0.235	13.0*	-10.2*	1.4
P2	0.209	0.239	0.212	14.2*	-11.1*	1.5
FTA measures	*2001*	*2007*	*2011/12*	*% Change 2001-2007*	*% Change 2007-2011/12*	*% Change 2001-2011/12*
Regular thresholds	0.318	0.336	0.325	5.8*	-3.1*	2.4*
Alternative thresholds	0.359	0.375	0.370	4.4*	-1.3*	3.0*

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. B-C indices are computed following equation (14) and TFA indices following equations (15)-(17). Percentage changes are computed as $100 * (P_{\propto,t} - P_{\propto,t-a})/P_{\propto,t-a}$. The alternative thresholds generate a wider range of values for which deprivation is partial, and are defined in table A4. Sample weights are applied to household observations to obtain nationally representative figures at the individual level. Stars indicate 5% significance of the changes, computed following Yalonetzky (2011).

Table 8: Household characteristics for Multidimensional (MD) and Money-metric (M) poor, by year

	All		MD poor	M poor	MD poor	M poor
	2001	2011	2001	2001	2011	2011
Household size	5.765	5.625	5.833	6.271	5.800	6.169
Number of children	2.625	2.560	2.773	2.992	2.767	2.980
Male	0.667	0.669	0.631	0.649	0.643	0.658
Married	0.765	0.754	0.749	0.761	0.727	0.748
Age	45.77	46.20	47.05	47.26	47.62	47.59
Primary education	0.525	0.403	0.585	0.581	0.481	0.472
Secondary education	0.337	0.495	0.245	0.258	0.403	0.417
Paid employee	0.263	0.172	0.183	0.178	0.0899	0.0910
Own account worker	0.520	0.558	0.654	0.627	0.711	0.696
No one with 7 or more years of education	0.0928	0.0577	0.128	0.107	0.0807	0.0669
Child not in school	0.0376	0.0251	0.0506	0.0485	0.0351	0.0330
Chronically ill	0.0944	0.163	0.114	0.0999	0.215	0.182
Did not get health care	0.0443	0.111	0.0577	0.0507	0.154	0.129
Unemployed	0.0818	0.0685	0.0619	0.0636	0.0515	0.0448
Far from services	0.291	0.288	0.389	0.311	0.397	0.335
Low asset index	0.609	0.557	0.807	0.693	0.766	0.669
No electricity	0.667	0.486	0.869	0.769	0.677	0.604
No toilets	0.324	0.314	0.448	0.395	0.435	0.398
Unprotected water	0.234	0.362	0.318	0.279	0.465	0.419
Wood as cooking fuel	0.737	0.716	0.921	0.838	0.899	0.853
Small land	0.101	0.0983	0.135	0.0826	0.0968	0.0800
Low TLU	0.261	0.332	0.357	0.281	0.413	0.367
Low rural equipment	0.206	0.227	0.286	0.218	0.280	0.247
Deprivation Count	2.569	2.645	3.345	2.852	3.488	3.049
Log pc consumption	7.223	7.060	7.053	6.814	6.828	6.630
Observations	19044	28920	12750	11065	21627	19081

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. Sample weights are applied to household observations to obtain nationally representative figures at the individual level.

Table 9: robustness tests performed on variables, weights and thresholds of the A-F multidimensional poverty indices

Robustness checks	Number of tests
Variables	
Exclude each variable	14
Exclude all rural/urban variables	1
Different assets variable (MCA and alternative indices)	2
Weights	
Use weights of 1	1
Use PCA weights	1
Use MCA weights	1
Thresholds	
Use lower thresholds	1
Use higher thresholds	1
Same thresholds urban/rural	1
Adjustment	
Without household size adjustment	1
M1 and M2 without adjustment	1
Total	**25**

Note: list of the robustness tests performed on the A-F indices for $k = 3$

Table A1: Breakdown of the A-F multidimensional poverty indices M_0, M_1 and M_2 by rural and urban areas, and percentage change

M_0												
k	2001		2007		2011/12		% change 2001-2007		% change 2007-2011/12		% change 2001-2011/12	
	U	R	U	R	U	R	U	R	U	R	U	R
1	0.128	0.325	0.131	0.349	0.135	0.326	1.8	7.5*	3.3	-6.7*	5.1*	0.3
2	0.087	0.310	0.094	0.332	0.096	0.304	7.5	7.2*	1.6	-8.5*	9.2*	-1.9*
3	0.050	0.238	0.058	0.275	0.060	0.239	17.1*	15.3*	2.8	-13.0*	20.3*	0.3
4	0.025	0.129	0.030	0.167	0.031	0.136	16.9	29.7*	5.1	-18.4*	22.9*	5.8*
M_1												
k	2001		2007		2011/12		% change 2001-2007		% change 2007-2011/12		% change 2001-2011/12	
	U	R	U	R	U	R	U	R	U	R	U	R
1	0.084	0.191	0.086	0.213	0.086	0.194	2.8	11.5*	0.3	-9.2*	3.1	1.2*
2	0.058	0.184	0.063	0.202	0.062	0.180	9.7*	9.9*	-2.3	-10.9*	7.2*	-2.1*
3	0.033	0.144	0.040	0.168	0.039	0.142	21.7*	16.7*	-2.3	-15.7*	18.9*	-1.7
4	0.017	0.080	0.021	0.104	0.020	0.081	24.1*	29.3*	-1.2	-22.1*	22.6*	0.7
M_2												
k	2001		2007		2011/12		% change 2001-2007		% change 2007-2011/12		% change 2001-2011/12	
	U	R	U	R	U	R	U	R	U	R	U	R
1	0.074	0.156	0.076	0.177	0.074	0.160	2.9	13.4*	-3.8	-9.5*	-1.0	2.6*
2	0.053	0.149	0.058	0.166	0.054	0.148	9.8*	11.4*	-7.2	-11.0*	1.9	-0.9
3	0.030	0.116	0.036	0.138	0.034	0.116	20.8*	18.1*	-6.4	-15.5*	13.1*	-0.2
4	0.015	0.064	0.019	0.084	0.018	0.066	22.7	31.1*	-4.5	-21.6*	17.2	2.8

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. Percentage changes are computed as $100 * (M_{\propto t} - M_{\propto t-a})/M_{\propto t-a}$. Sample weights are applied to household observations to obtain nationally representative figures at the individual level. Stars indicate significance of the changes at 5%, computed following Yalonetzky (2011).

Table A2: regional decomposition of A-F multidimensional poverty index M_0 for $k = 3$

Region	2001	2007	2011	2001-2007	2007-2011	2001-2011
Bulawayo	0.018	0.024	0.068	0.006	0.044	0.050
Manicaland	0.178	0.239	0.201	0.060	-0.038	0.023
Mashonaland Central	0.201	0.216	0.214	0.015	-0.002	0.013
Mashonaland East	0.227	0.222	0.217	-0.005	-0.005	-0.009
Mashonaland West	0.241	0.240	0.230	0.000	-0.010	-0.011
Matabeleland North	0.261	0.332	0.284	0.071	-0.048	0.023
Matabeleland South	0.209	0.266	0.241	0.057	-0.025	0.032
Midlands	0.209	0.204	0.189	-0.005	-0.016	-0.021
Masvingo	0.229	0.322	0.255	0.093	-0.067	0.026
Harare	0.055	0.082	0.069	0.028	-0.013	0.015
Zimbabwe	*0.180*	*0.216*	*0.192*	*0.036*	*-0.024*	*0.012*

***Source*: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. Sample weights are applied to household observations to obtain nationally representative figures at the individual level. Changes on the right panel are row differences between two years' M_0 indices.**

Table A3: Cross-tabulation Multidimensional (MD) and Money-metric (M) poor

	MD poor			M poor			MD poor			M poor		
	2001 All	2001 Rural	2001 Urban	**2001 All**	2001 Rural	2001 Urban	**2011 All**	2011 Rural	2011 Urban	**2011 All**	2011 Rural	2011 Urban
MD Poor	**1**	1	1	**0.785**	0.893	0.342	**1**	1	1	**0.799**	0.860	0.437
M Poor	**0.785**	0.807	0.605	**1**	1	1	**0.799**	0.828	0.572	**1**	1	1
M Non-Poor	**0**	0	0	**0.215**	0.107	0.658	**0**	0	0	**0.201**	0.140	0.563
MD Non-Poor	**0.215**	0.193	0.395	**0**	0	0	**0.201**	0.172	0.428	**0**	0	0
Observations	12754	11089	1665	11065	8521	2544	21627	20249	1378	19081	17443	1638

Source: our calculations with 2001, 2007 and 2011/12 ICES/PICES data. Sample weights are applied to household observations to obtain nationally representative figures at the individual level. multidimensional poor are those poor for $k = 2$ and the poverty line is adjusted to obtain the same proportion of money-metric poor in the population in both 2001 and 2011.

Table A4: Alternative Thresholds for A-F multidimensional poverty indices $M_{\propto}$ and TFA measures (continuous variables)

Variable (range)	Regular threshold	Lower thresholds $M_{\propto}$	Higher thresholds $M_{\propto}$	Regular Thresholds TFA (min-max)	Alternative Thresholds TFA (min-max)
Maximum year of education in the household (0+)	7	5	9	5-9	0-14
Age of the child not enrolled at school (age-7: 0+, threshold: <5)	12	9	15	9-15	7-18
Toilet quality index from (0-4)	2	2 (no change)	4	2-4	1-4
Source of water quality index, depending on water source and distance to the source (0-9)	5	3	7	3-7	1-8
Cooking fuel quality index = 0 (wood and similar), 1 (paraffin, etc.) or 2 (electricity)	1	1 (no change)	2	1-2	1-2
Asset index, cf. description in text (0-8)	2	1	3	1-3	1-8
Land size (0+)	0.25	0.1	0.5	0.1-0.5	0.1-5
TLU, cf. description in text (0+)	1	0.25	1.5	0.25-1.5	0.1-6
Number of close services, cf. description in text (0-7)	6	4	7	4-7	1-7
Rural equipment	1	1 (no change)	2	1-2	1-3

Table A5: Treatment of missing values and size of household weighting for the A-F multidimensional poverty indices $M_{\propto}$

Variable	Treatment of missing values: missing if…	Adjustment for size of the household *i*
Nobody in the household completed 7 years of education	… education achievement is missing for strictly more than 1/3 of the household members above 7 AND if other members did not complete 7 years of education	$aw_i = (\frac{n_i}{\bar{n}})^{1/2}$ where n_i is the number of individuals above 13 in the household and $\bar{n}$ is the sample median of individuals above 13
The household has one child below 12 not enrolled in school	… schooling status of the primary-school-aged child is missing	$aw_i = (\frac{\bar{n}}{n_i})^{1/2} * cne$ where n_i is the number of household's primary-school-aged children, cne is the number of them not enrolled and $\bar{n}$ is the sample median primary-school-aged children
One member of the household is chronically ill	… illness information t is missing for strictly more than 1/2 of the household members AND if no other member is chronically ill	$aw_i = (\frac{\bar{n}}{n_i})^{1/2} * ci$ where n_i is the household size, ci is the number of members chronically ill and $\bar{n}$ is the sample median household size
One member of the household has been ill but did not get health care in the last 30 days	… illness information t is missing for strictly more than 1/2 of the household members AND if no other member was ill with no health care	$aw_i = (\frac{\bar{n}}{n_i})^{1/2} * nhc$ where n_i is the household size, nhc is the number of members who were ill but did not get health care, and $\bar{n}$ is the sample median household size
One member of the household was unemployed in the last 12 month	… main activity is missing for strictly more than half of the household members above 9 who are not enrolled in school	$aw_i = (\frac{\bar{n}}{n_i})^{1/2} * ue$ where n_i is the number of household adults, ue is the number of those unemployed and $\bar{n}$ is the sample median adults
The household is far from a services	… distance to services is missing for strictly more than 2 service	No adjustment

Table A6: Variables and threshold for the A-F multidimensional poverty indices M_{α}

Dichotomous Variable	Cardinal Variable (range)	Threshold
Nobody in the household completed 7 years of education	Maximum year of education in the household (0+)	<7
The household has one child below 12 not enrolled in school	Age of the child not enrolled at school (age-7: 0+, threshold: <5)	>6 <12
One member of the household is chronically ill	N/A	
One member of the household did not get health care	N/A	
One member of the household was unemployed the last 12 month	N/A	
The house does not have electricity	N/A	
The house does not have toilets	Toilet quality index from (0-4)[36]	<2 (rural: no pit/blair/flush toilet; urban: no flush toilet)
The source of water of the household is an unprotected well (or worse) or farther than 1 km away	Source of water quality index, depending on water source and distance to the source (0-9)[37]	<5 (rural: source is unprotected well or distance > 1km; urban: communal tape on premise or piped water)
The household cooks with wood	Cooking fuel quality index = 0 (wood and similar), 1 (paraffin, etc.) or 2 (electricity)	<1
The asset index of the household is below a given threshold	Asset index, cf. description in text (0-8)	<2
The household has less than 0.25 hectares of land	Land size (0+)	<0.25
The animal index of the household is below a given threshold (<1 TLU)	TLU (0+)	<1
Rural equipment	Equipment index, cf. description in text (0-5)	<1
The household is far from a certain number of services	Number of close services (0-7)	<6

[36] The index increases when the toilet improves from no toilet to pit toilet to blair toilet to flush toilet.

[37] The index increases when the water source improves from river/stream/dam to well-unprotected to borehole/protected well to communal tape to piped water outside to piped water inside the house; and when the distance decreases to less than 1km.

Table A7: Weights adjustment to construct g_1 and g_2 for the multidimensional poverty indices $M_{\propto}$

	Original weights (urban)	Original weights (rural)	Adjustment (urban)	Adjustment (rural)	New weights (urban)	New weights (rural)
Education maximum	1	1	0.5	0.5	1.5	1.5
Education dropout age	1	1	0.5	0.5	1.5	1.5
Chronic illness	1	1	-0.5	-0.5	0.5	0.5
No health care	1	1	-0.5	-0.5	0.5	0.5
Unemployment	1	0	-0.25	0	0.75	0
No electricity	1	0.5	-0.25	-0.35	0.75	0.15
No toilet	0.5	0.5	0	0	0.5	0.5
No clean water	0.5	0.5	0.25	0.25	0.75	0.75
Wood as cooking fuel	0.5	0.5	-0.25	-0.25	0.25	0.25
Low assets	1	1	0	0	1	1
Small land	0	0.5	0	0.1	0	0.6
Low TLU	0	0.5	0	0.1	0	0.6
Low rural assets	0	0.5	0	-0.35	0	0.15
Far from services	1	1	0.5	0.5	1.5	1.5

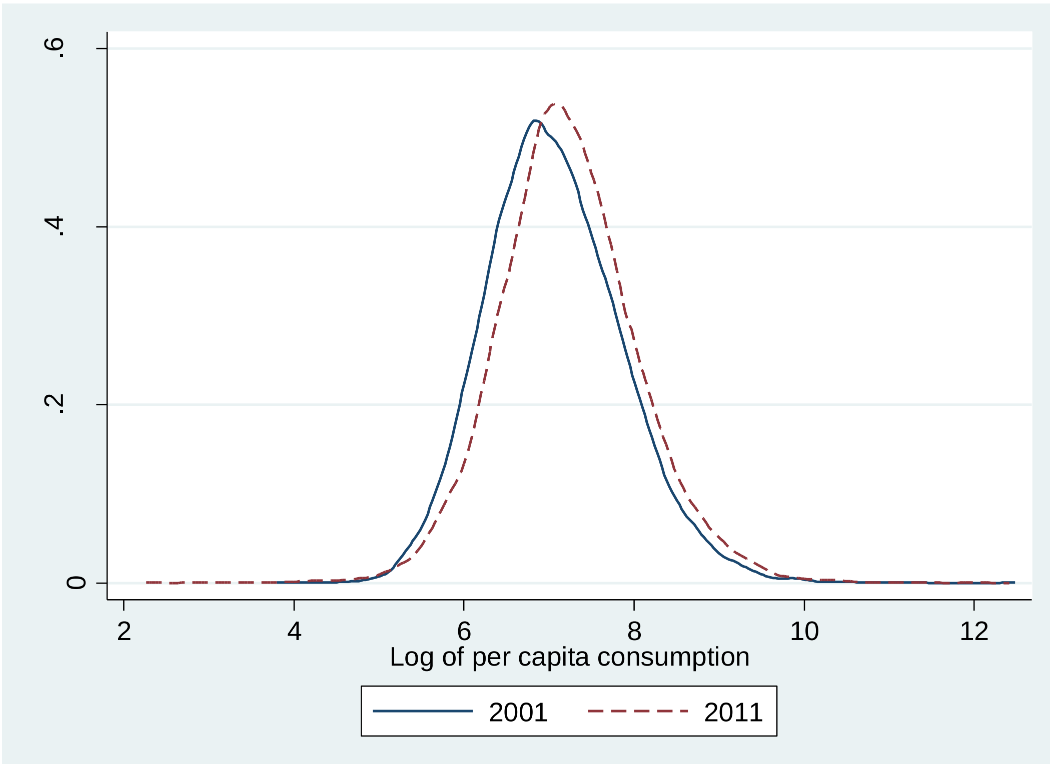
Table A8: Items used for the construction of the price deflator for the money-metric poverty measures

Commodity	Share of minimum needs food basket	Quantity (kg/annum/person)
Maize (including own-consumed)	0.28	134.7
Bread	0.06	18.3
Rice	0.01	0.7
Flour	0.02	3.6
Beef	0.12	11.1
Poultry	0.02	2.4
Fish	0.05	3.5
Milk	0.05	15.5
Cooking oil	0.06	5.7
Rape	0.03	13.1
Cabbage	0.01	5.3
Tomatoes	0.01	3.1
Own-consumed vegetables	0.18	66.7
Potatoes	0.02	6.6
Sugar	0.08	13.3
Beans	0.01	10.5
Salt	0.01	2.9

Source: ZIMSTAT (2013).

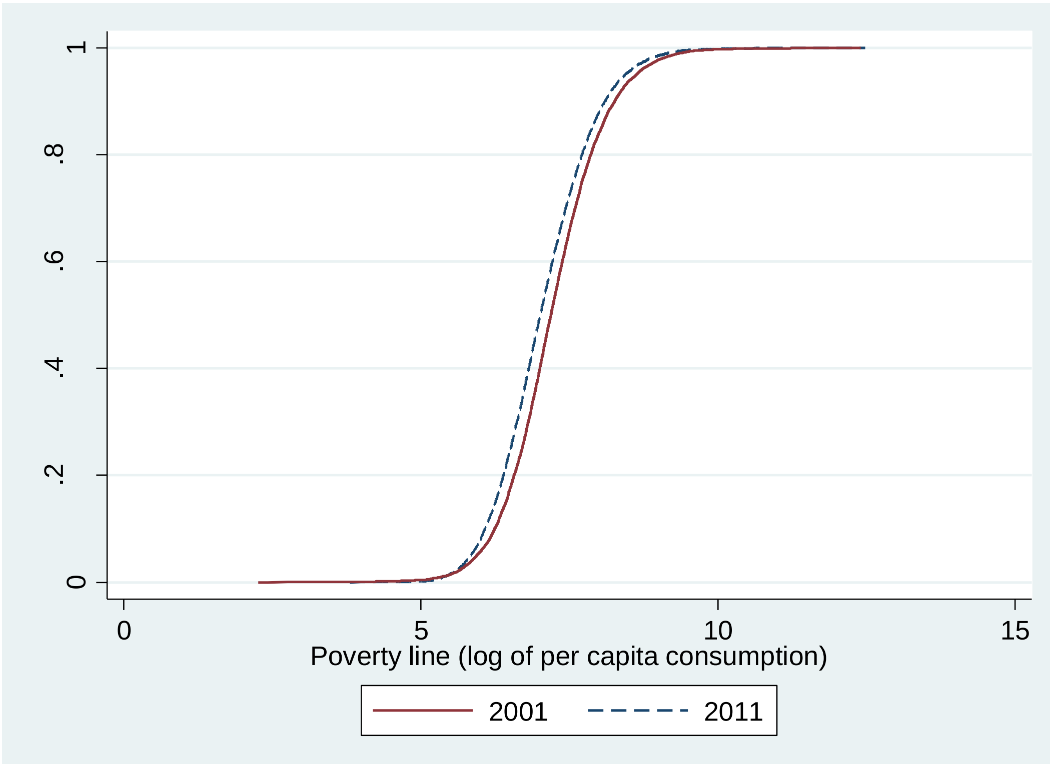
Figures

Figure 1: Smoothed density of log of per capita consumption, 2001 and 2011/12



Source: our calculations with 2001 and 2011/12 ICES/PICES data. Sample weights are applied to household observations to obtain nationally representative figures at the individual level.

Figure 2: Money-metric poverty incidence as a function of the poverty line



Source: our calculations with 2001 and 2011/12 ICES/PICES data, using pov_robust.ado on Stata. Sample weights are applied to household observations to obtain nationally representative figures at the individual level.

ESSAY 2: Reaching the poor: an ex-post comparison of targeting mechanisms in Cameroon

1. Introduction

Targeting to the poor accurately and efficiently is central to any poverty alleviation policy, and is particularly crucial for building well-functioning social safety nets systems. Because poverty is not readily defined or easily observable, reaching the poor poses challenges in terms of knowledge (identify the poor) and mechanism (ensure that they are beneficiaries of the policy). The rise of development interventions directly addressed to individuals or households– such as asset, food and cash direct transfers– emphases these two challenges faced by governments and development practitioners in terms of both knowledge and mechanism. Targeting is inherently inexact in practice: it includes 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 has critical implications for both the local impact of projects and the broad success of national social assistance policies. Thus it is not surprising that choice of targeting mechanism can generate fierce debates among policy makers, civil society stakeholders, and academics (Coady, Grosh, and Hoddinott 2004, Grosh et al. 2008, Mkandawire 2005).

In this context, the government of Cameroon has decided to move away from universal subsidies on fuel and food prices, which had been proven regressive (World Bank 2011a). Previous studies have shown a high potential for improvement of social assistance targeting by using geographic and Proxy Means Testing (PMT) to reach poor individuals in Cameroon (Stoeffler, Nguetse-Tegoum, and Mills 2013), but the ex-post efficiency of targeting mechanisms have rarely been assessed in Sub-Saharan Africa. In addition, there exists a tension among practitioners employing targeting methods based on statistical formulas (such as PMT targeting) and those relying on community participation. There are few rigorous empirical comparisons of targeting outcomes to inform the debates. This paper fills this gap by studying the targeting efficiency of the Social Safety Nets Pilot Project (SSNPP), an unconditional cash transfer project in rural, northern Cameroon.

The SSNPP employs a hybrid targeting which combines two popular targeting methods: Proxy Means Testing (PMT) (using a statistical formula) and Community Based Targeting (CBT) (through village assemblies). This pilot project runs in 15 villages and delivers regular cash transfers to 1,500 households (about 35% of these villages population) which have been selected both by the PMT, because their PMT score generated by the formula is above a certain threshold, and by the community. The objective of this paper is to understand and assess the performance of targeting mechanisms employed in the project, in order to improve the targeting system in Cameroon and elsewhere. To do so, the article analyses data collected from 2,084 households, which are identified as poor by the PMT, the community, both or neither. Thus, the article is unique in studying ex-post targeting outcomes of an implemented social safety nets project (rather than an experiment). Moreover, the data allows us to observe actual identification of households for program eligibility under two different targeting mechanisms, PMT and CBT. The article also explores the determinants of erroneous exclusion and inclusion and possible complementarities of PMT and CBT to reduce exclusion and inclusion errors. Also unique is the fact that PMT formula efficiency is not assessed with the national survey from which it was constructed, but from a new, local dataset that is entirely comparable to the national one from which the PMT has been designed. Finally, because of an unanticipated gap in the implementation timeline, targeting is assessed one year after eligibility determination, but before project implementation, allowing us to analyze targeting performance in the medium-term without the shift in consumption introduced by program intervention.

This analysis is conducted in two steps. First, we use popular targeting efficiency indicators – such as percentage errors of inclusion and exclusion, and simulated impact on poverty indices – to evaluate the extent to which community and the PMT targeting successfully identify the poor.[1] Second, we look for characteristics associated with errors of exclusion and inclusion (to identify the households most likely to be erroneously classified as non-poor or poor) in order to improve targeting systems. In the same way, we try to understand which factors drive community choices by looking at if additional information known by the community (such as the vulnerability to shocks or access to specific sources of income) has an impact on its decisions, and systematically explore mismatch between community and PMT selection. The aim of the analysis is to assess the potential for improved targeting through integrated PMT and CBT methods.

Results suggest a relatively poor efficiency of community targeting in the context of the SSNPP, and a slightly better performance of PMT targeting in identifying households with low per capita consumption. Also, hybrid targeting does not identify poor households better than PMT alone according to all the indicators employed. However, community choice seems to be driven by different factors associated with poverty such as income potential – which includes human and physical capital. Divergence between community and PMT targeting suggests strong complementarities between the two methods, but these complementarities do not lead to a greater targeting efficiency of hybrid targeting in Soulédé-Roua.

The next section situates the analysis in the literature on targeting, particularly empirical studies of PMT and community targeting performance. Section three presents the project and the data on

[1] In this paper, to assess targeting efficiency, poor households are defined as those below the appropriate poverty line in terms of per capita consumption (see section 4). Alternative poverty definitions are used as robustness tests.

which the analysis is based. Section four describes the targeting indicators employed and the empirical approach. Section five presents results, and the last section discusses policy implications and concludes.

2. Proxy means testing and community targeting

With the rise of formal methods for social assistance targeting, a large literature emerged on the issue in the 1990s, as well as several empirical case studies more recently. This literature has not been particularly conclusive regarding what method in what situation works best for reaching the poor. While targeting specific individuals appears as an efficient way for social assistance programs to allocate scare resources to the poor, the inherent errors of targeting methods (they never perfectly reach their target) generate questions regarding the best way do so (Besley and Kanbur 1990, Van de Walle and Nead 1995). In particular some argue, it may be preferable to provide universal rather than targeted benefices to the population (such as social pensions) for reasons related to cost-effectiveness of interventions, the political economy of targeting, and the intended scope of social assistance (Mkandawire 2005). However, there are strong budgetary arguments against universalism, and its political acceptability (or even interest) may be limited for projects such as unconditional cash transfers (Del Ninno and Mills 2014, Ferguson 2013). Several formal targeting methods are used in social assistance programs– and often combined in hybrid mechanisms. These different methods are reviewed and compared by an influential meta-study which uses a constructed database of 122 antipoverty interventions to compare their targeting outcomes (Coady, Grosh, and Hoddinott 2004). This meta-study does not provide strong evidence that one targeting method works better than the others: the authors found instead wide variations in targeting performance within each method, suggesting that targeting performance is strongly linked to program context and implementation. PMT and CBT have been the most widely used targeting methods in the last decade and are seen as promising (Slater et al. 2009). These two methods are the focus of this paper.

Proxy means testing (PMT) gained popularity in the 1990s because of its potential for a greater impact on poverty than existing social assistance programs, relying for instance on universal subsidies (Grosh and Baker 1995). There are several reasons for the popularity of this method based on a statistical formula and household's characteristics: i) PMT is relatively cheap and simple to implement because it is based on a limited set of characteristics easy to observe and verify; ii) it relies on "objective" criteria, which gives to the targeting system credibility, fairness and robustness to manipulation; iii) it is based on indicators correlated with long-term well-being and not only short-term consumption, which helps to identify the chronic poor; iv) by the same token, PMT generates less disincentives to increase income, work participation, etc. than other methods. For these reasons, PMT targeting is currently widely implemented in Sub-Saharan Africa (Del Ninno and Mills 2014), often combined with other targeting methods (Pop 2014). PMT most advanced versions (PMT plus), which have not been implemented yet, also try to identify households vulnerable to short-term shocks (Groover 2014).

Concretely, PMT targeting has two distinct steps. First, a PMT formula is designed from nationally representative datasets: household characteristics (such as household size, roof material, number of animals) are given a certain weight (through regression-based analyses usually) so that they can predict household welfare. Second, a short survey containing the formula items is collected among potential beneficiaries to compute their PMT score, which serve as proxy for household income, welfare or poverty level. The first step is usually subject to ex-ante simulations to assess the potential of the formula for adequately targeting the poor (based on the same nationally representative dataset), while ex-post evaluation of the targeting efficiency can be performed after the second step. Simple ex-ante arithmetic simulations have shown the potential, but also the limits of targeting in Egypt (Ahmed and Bouis 2002), Sri Lanka (Narayan and Yoshida 2005), Bangladesh (Sharif 2009) or Senegal (Leite, Stoeffler, and Kryeziu 2013), since inclusion and exclusion errors are usually above 20% (and sometimes close to 50%).[2] Because of its embodied errors, implementation issues, and exclusion of the community from the targeting process, PMT targeting has also gained many opponents (Kidd and Wylde 2011).

Community based targeting overcomes some of the weaknesses of PMT targeting, in particular its exclusion of the community from the targeting process. CBT involves a participatory process from the communities which receive social assistance programs in the selection of the beneficiary households at the local level. Usually, a detailed process is designed by the program managers so that community elite meet in a village assembly and construct a list of poor households which will be beneficiaries of the program – with check and balances to limit clientelism and elite capture. Thus, community targeting has the advantage of: i) bringing more *information* from the community, compared to a "blind" formula or criteria (Alderman 2002); ii) involving the community in a participatory process, which aims at generating adhesion to the program; iii) being more transparent for the potential beneficiaries, it is supposed to generate more agreement on the selection outcome.[3] It has been widely used in Sub-Saharan Africa (Garcia and Moore 2012).

[2] Simple arithmetic simulations look at the impact of the program on Foster-Greer-Thorbecke (FGT) poverty indices under different scenarios. Dynamic simulations have also been performed to assess the *impact* of cash transfer programs rather than *targeting* efficiency (Bourguignon, Ferreira, and Leite 2003, Stoeffler 2013).

[3] In programs using PMT targeting, the targeting process is not always understood locally (Adato and 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.

From a general point of view, both targeting methods and targeting *per se* have been criticized on several grounds. Targeting cost (public and private), inaccuracy and inefficiency have been pointed out, as well as the negative institutional and political economy consequences and it undesirable philosophical implications (Mkandawire 2005, Sen 1995). When poverty rates are very high ("everybody is poor here"), transferring resources to a very small proportion of the poor also poses questions of fairness, particularly when this transfer causes beneficiary households to become much wealthier than households just a little better-off than they were initially in the wealth distribution (Ellis 2012). Some critics have focused on the errors embodied in the mechanism of PMT targeting itself (especially when the share of the population covered is low), its implementation issues, and its social and political costs (Kidd and Wylde 2011) . Other have denounced elite capture, community tensions, clientelism and other implementation issues inherent to community targeting in practice (Olivier de Sardan 2013, Conning and Kevane 2002) and to community-driven development in general (Mansuri and Rao 2004). PMT targeting has also been shown to be subject to corruption, which decreases its expected efficiency (Niehaus and Atanassova 2013). Finally, the *consequences* of mistargeting have been shown in a large Indonesian cash transfer program, where targeting inclusion errors (leakages to non-poor) generated crime and destroyed social cohesion (Cameron and Shah 2014).[4]

While not fully addressing the political economy consequences of targeting, a recent literature has been interested in the careful empirical study of targeting at the micro-level. This literature allowed a better understanding of costs, efficiency, and distribution outcomes of several targeting methods. A study of community (hybrid) targeting in three Sub-Saharan countries shows it to be been progressive in the projects studied (Handa et al. 2012). Combining community targeting

[4] Another type of critics regards targeting indicators used in the literature, which should focus on success in terms of poverty alleviation rather than (instrumental) *targeting* efficiency (Ravallion 2009).

with categorical targeting improves the overall efficiency in Malawi, but not so much in Kenya and Mozambique. In Kenya, community targeting was found mildly progressive and outperformed categorical targeting, but PMT targeting has the potential to perform better, based on ex-ante simulations (Sabates-Wheeler, Hurrell, and Devereux 2014). A cash grant experiment conducted in Zambia tested several hypotheses and showed that poverty motives prevail over egalitarian ones and that elite capture seems very limited (Schüring 2014). However, in terms of the share of transfers allocated to the poor, targeting is only mildly progressive, and success depends on several factors including community cohesion, trust, level of information and experience with prior targeting exercises. A study of a conditional cash transfer (CCT) program in Nicaragua shows that its targeting method, which combines PMT and geographic targeting, generates limited errors of inclusion and exclusion (Maluccio 2009).

Studies comparing PMT and community targeting ex-post do not usually find that one method clearly dominates the other. In a comparison of community targeting with two PMT formulas in Peru and Honduras, none of these methods clearly outperforms the others, neither do they significantly differ from random selection of beneficiaries, in terms of the per capita consumption of beneficiaries (Karlan and Thuysbaert 2013). When different measures of poverty are used (such as an asset index), they perform slightly better than random selection, and community targeting is driven by household characteristics in addition to poverty status.[5] Based on a small dataset, an assessment of a targeting method including Participatory Rural Appraisal in India performs better than most national social assistance programs in terms of various poverty metrics, but not per capita consumption (Banerjee et al. 2007). In a study of a social safety nets program in Ghana, both PMT and CBT have been shown to be progressive, but leave many poor and extreme-poor uncovered (Pop 2014). Interestingly, community preferences

[5] The community targeting outcome also suggests some elite capture.

explain part of the differences found between the two methods: CBT favors small households by selecting elderly without support and disabled individuals, while the PMT formula favors large households. One of the most complete targeting studies is a large field experiment randomly allocating villages to three distinct targeting methods in Indonesia (Alatas et al. 2012). It shows that PMT targeting performs better than community and hybrid targeting in terms of errors of exclusion or inclusion, but that the difference is too small to affect the expected impact of the transfers on poverty indices. Besides, community targeting generates higher satisfaction in the program villages and is driven by a different conception of poverty.[6] Elite capture is not found in the experiment, and hybrid targeting performs worse than each of the other methods separately, while being more expensive. Our paper contributes to this emerging literature by bringing additional evidence on major outstanding questions: the relative performance of PMT and CBT in an actual program in rural Sub-Saharan Africa, and the systematic differences in inclusion and exclusion errors. It does so by studying the ex-post targeting outcome of a cash transfer project implemented by the government of Cameroon in a rural, very poor Sahelian environment where household eligibility status has been assigned simultaneously through PMT and community mechanisms.

3. Project description and data

The past ten years have seen a rise of social safety nets programs in Sub-Saharan Africa aiming at providing support to poor and vulnerable households. This transition towards the provision of reliable and regular support to poor and vulnerable households has been accompanied by strong efforts to improve the current mechanisms employed to target these households (Monchuk 2013). The unconditional cash transfer (UCT) project whose targeting process is analyzed in this

[6] The lower performance of community targeting (in terms of exclusion and inclusion errors measured in per capita consumption) is also due to the “tiredness” generated by the process: community targeting performs better at the beginning of the targeting meetings, but deteriorates during the second half of the meetings.

paper is part of the emerging SSN policy in Cameroon. While the country has seen robust recent economic growth, poverty has remained persistently high in the previous decade: poverty incidence has been stable between 2001 (40.2%) and 2007 (39.9%) (World Bank 2011a). Chronic poverty has been estimated at 26.1% and is concentrated in the rural and northern regions of Cameroon. Social assistance has been mostly *ad hoc*, lacking coordination and with low coverage: SSN account for only 0.23% of GDP excluding subsidies (World Bank 2011b). Subsidies on fuel and food price are very costly and have been shown to be regressive, therefore the government of Cameroon is now moving towards a unified SSN system, where UCTs targeted to the poor constitute a central part. Thus, the targeting efficiency of this social safety net is critical to improve the current system and ensure a sustainable and cost-effective cash transfer system.[7]

The Social Safety Nets Pilot Project (SSNPP) is an UCT project which started in December 2013. It provides beneficiary households with 15,000 FCFA monthly, an amount chosen to represent about 20% of average poor households consumption expenditures (Nguetse-Tegoum and Stoeffler 2012). In order to focus on the poorest households in Cameroon while testing different instruments, the SSNPP has combined geographic, PMT and community targeting.[8] This paper focuses on targeting at the household level in the 15 villages selected for the UCT pilot project where PMT and community targeting are employed simultaneously. The poverty (eligibility) status of each household is evaluated by PMT and by the community separately, and the set of beneficiary households is the intersection of the households selected by the community

[7] Targeting accuracy is also likely to be critical for the social and political acceptability of the polity shift from universal subsidies to targeted transfers.

[8] Geographic targeting has been used to choose Soulédé-Roua as the project area, because it is the poorest arrondissement in the country; and then meeting with community elites and officials resulted in the choice of the poorest 15 villages (out of 34 villages in total in Soulédé-Roua) as beneficiary villages. Criteria for the choice of villages include infrastructures (access to electricity, clean water, etc.), access to the main road, and perceived households' poverty level as defined below.

and selected by the PMT. The community had to select (roughly) 70% of the village households as poor, while the PMT threshold would be adjusted so that 35% of the households would be beneficiaries of the SSNPP and receive cash transfers. There is a common (unique) PMT score threshold for the SSNPP, so that the percentage of beneficiaries can vary by village.

Community targeting followed a rigorous process set up by the SSNPP Project Management Unit (UGP). Local Targeting Groups (GLC) were created in each village, and GLC members cannot be beneficiaries themselves. Forums and workshops are 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 (day laborers) of the village households, geographic access and population density (lack of access to agricultural land). The GLC members produce lists of eligible (poor) households, and their work is checked by Citizen Control Groups (GLCC). At the *arrondissement* level (Soulédé-Roua), a *Commune* Working Group (GTC) records complains from the GLCC, manages the community targeting list and transfers it to the UGP. It is important to note that the selection target of 70% of households per village was not followed by GLCs, and that actual selection rates range from 26% to 100% of the village households, depending on the village.[9]

The PMT formula used in the SSNPP has been created from a nationally representative dataset collected in 2007, the *Enquete Camerounaise Aupres des Menages 3* (ECAM3). The rationale is to use variables which are easy to collect and verify to predict the household poverty status– measured in per capita consumption expenditures. These variables include household

[9] It would have been desirable to ask the community to rank households rather than dividing them in two discrete categories (selected or not as poor). However, the pilot project did not require the community to conduct a time-consuming exhaustive ranking. These rankings have been proven useful for targeting analysis, but issues arise regarding the accuracy of the last households ranked compared to the first ones (Alatas et al. 2012).

characteristics, housing conditions, assets, etc., so that it takes into account long-term determinants and correlates of poverty along multiple dimensions. The formula generates a score which correspond to the probability that a household is chronically poor, so that a high score represents a higher predicted degree of poverty (Stoeffler, Nguetse-Tegoum, and Mills 2013, Nguetse-Tegoum and Stoeffler 2012). Based on this formula, a score is generated for each household in the 15 beneficiary villages. Adjusting the eligibility threshold allows to obtain the desired number of beneficiaries for the project.

Thus, the analysis in this paper relies on two sources of data. The PMT data has been collected through a short survey containing only the variables necessary for computing household PMT scores in December 2012, and community targeting occurred at the same time. The second source of data is the baseline survey of the impact evaluation, collected in December 2013 among 2,084 households in Soulédé-Roua.[10] The sample was stratified, based on the PMT/community survey, in order to include 828 beneficiaries, 628 non-beneficiaries targeted by the community and 628 other non-beneficiaries. 1,758 usable observations are kept for the analysis and sample weights used to take into account the stratification. 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) used to design the PMT formula, in order to ensure comparability with previous poverty analyses and between ex-ante and ex-post

[10] 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, independently of short-term negative or positive shocks which occurred when targeting was conducted.

results.[11] Unfortunately, the survey (design primarily for the impact evaluation) does not include information on household's satisfaction or complains regarding the targeting process and outcomes.

In our sample, 720 households (41.79%) are selected by both the community and the PMT, and 117 households (6.79%) are selected by neither. 443 households (25.71%) households are selected by the community only, and the same number is selected by the PMT only. Household characteristics for the whole sample and by targeting group are presented in Table 1. Overall, 53.7% of Soulédé-Roua individuals are selected by the community, and 34.1% are beneficiary of the project (hybrid targeting). Households are large (7.5 members on average) and male-headed (80.1%) on average. Most household heads went to primary school (59.6%) and are either Christians (41.7%) or Animists (41.3%). Household exposure to shocks is frequent, with most households affected during the last 12 months (69.1%). Most people have livestock (77.5%), with 0.73 Tropical Livestock Units (TLU) as average (i.e. one cow).[12] Land is scarce with households exploiting 0.88 ha on average and more than half of the households renting land (50.9%). Most individuals live in households without any physical assets (71.0%) and know either moderate (38.9%) or severe (17.8%) hunger according to the Household Hunger Score (HHS). Overall, most households in Soulédé-Roua seem to experience important deprivations. However, there are not clear differences between different targeting groups on average in terms of household characteristics, suggesting that a more controlled evaluation of targeting performance is needed.

4. Targeting indicators and empirical strategy

[11] The survey was also conducted by the same institution (Institut National de la Statistique) following identical protocols.

[12] The TLU formula is:

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

A. Targeting efficiency indicators

If the "poor" are the targeted population, assessing targeting efficiency means, conceptually, considering two types of errors: poor households that are incorrectly excluded by the program and non-poor households erroneously included in the program. From a policy point of view, both errors are important. Inclusion errors ("leakages") mean that resources are diverted from the poor to the non-poor, and are likely to generate a sentiment of unfairness or even social unrest (Cameron and Shah 2014). Exclusion errors means that some poor households do not benefit from the program, which undermines program impact (Cornia and Stewart 1993).

Various meaningful indices have been used in the literature to measure these efficiency errors or targeting efficiency. Table 2 illustrates leakage and undercoverage. Leakage refers to inclusion errors (IE) (or Type 1 errors), i.e. households which are beneficiaries of the program but should not be (they are not poor). Undercoverage refers to exclusion errors (EE) (or Type 2 errors), i.e. households which are not beneficiaries of the program but should be (they are poor). Based on Table 2, an IE index measures the share of non-poor beneficiaries over the total number of beneficiaries: $IE = \frac{E1}{B}$. Similarly, a EE index measures the share of poor non-beneficiaries over the total number of poor: $EE = \frac{E2}{P}$. It is then possible to compare targeting efficiency a given method j (IE_j and EE_j) with an alternative method k (IE_k and EE_k).[13]

Inclusion and exclusion errors can be synthetized in a slightly different manner with a single index called Targeting Differential (TD), which represents the difference between the share of the poor and the non-poor participating to the program (Galasso and Ravallion 2005):

[13] Among these methods, we consider random targeting r (where $\mathrm{E}(IE_r) = \frac{NP}{T}$ and $E(EE_r) = \frac{NB}{T}$), universal targeting (where $\mathrm{E}(IE_r) = \frac{NP}{T}$ and $E(EE_r) = 0$) and other fictional targeting methods for comparison purposes (see below).

$TD = \frac{C1}{P} - \frac{E1}{NP}$ 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 is comprised between -1 and 1 with $\mathrm{E}(TD) = 0$ when targeting is either random or universal. Another popular index employed to synthetize inclusion and exclusion efficiency of a targeting mechanism is the share of resources actually transferred to the poor: the CGH index (Coady, Grosh, and Hoddinott 2004). This index measures the amount of resources transferred to the poor (or to a given poorest percentile of the population) over the total amount transferred by the program. It is then divided (normalized) by the share of the poor (or of the percentile considered) 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 considered (chosen). CGH_x is comprised between 0 (if all resources are transferred to the non-poor) and $\frac{100}{x}$ when all resources are transferred to the poor, with $\mathrm{E}(CGH_x) = 1$ in case of universal or random targeting.

All these targeting indices are based on a basic classification of households as poor or not-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 are. 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 from the poverty line (extremely poor). For that reason, we suggest a new index TD_α which extends the simple TD by taking into account how far from the poverty threshold participants' per capita consumption is. It is similar to the Foster-Greer-Thorbecke poverty indices in that it considers the gap to the threshold to the power α. For a given targeting mechanism j:

$$TD_{\propto,j} = \sum_i \frac{P_{i\in J} * \left\{\left|\frac{z-c_i}{z}\right|\right\}^{\propto}}{P_i} - \frac{NP_{i\in J} * \left\{\left|\frac{z-c_i}{z}\right|\right\}^{\propto}}{NP_i}$$
$$= \{\left|\frac{z-c_i}{z}\right|\}^{\propto} \left[\frac{P_{i\in I}}{P_i} - \frac{NP_{i\in I}}{NP_i}\right]$$
where, 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.

The TD incidence (TD_0) is the index proposed by Galasso and Ravallion (2005):

$$TD_0 = TD = \sum_i \frac{P_{i\in J}}{P_i} - \frac{NP_{i\in J}}{NP_i}$$
Also, the $TD_{\propto}$ index can also be decomposed into its 2 components to show if a targeting mechanism is efficient (inefficient) because of its inclusion of poor (non-poor) households or because of its exclusion of non-poor (poor) households:

$$TD_{\propto,j,poor} = \sum_i \frac{P_{i\in J} * \left\{\left|\frac{z-c_i}{z}\right|\right\}^{\propto}}{P_i}$$
$$TD_{\propto,j,non-poor} = \sum_i \frac{NP_{i\in J} * \left\{\left|\frac{z-c_i}{z}\right|\right\}^{\propto}}{NP_i}$$
Finally, the efficiency of each targeting method is assessed in terms of its potential impact on poverty reduction. For this, transfers to households selected by each targeted method are simulated and their new per capita consumption expenditures are computed, adding the transfers to their actual (pre-transfer) expenditures. The difference between pre-transfer and new poverty indices is computed for Foster-Greer-Thorbecke (FGT) (1984) poverty indices:

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

where i is a particular targeting method and $\alpha = 0,1,2$ for poverty incidence, gap and severity. This indicator allows not only to measure how well poor individuals are identified by a targeting method (which is valuable per se), but also what is the expected consequence on poverty reduction of this targeting efficiency (or inefficiency). In this context, poverty gap and severity ($\alpha = 1,2$) are most relevant, because a greater impact on the poverty incidence from a targeting method may indicate that the method reaches households closer to the poverty threshold. This outcome is arguably in terms of worse targeting efficiency since households closer to the threshold are better-off than those farther below the threshold.

While these indices offer simple methods to compare the efficiency of different targeting methods, making this comparison meaningful is not straightforward. First, different programs or targeting methods may not target the same share of the population (or number of households), which has an impact on inclusion and exclusion errors. For instance, a PMT targeting method using a threshold aiming at having 10% of the households as beneficiaries is expected to have a much higher level of errors than the same PMT targeting method using a higher threshold, for instance selecting 40% of the population (Kidd and Wylde 2011). Second, an appropriate definition of poverty is needed to construct the matrix in Table 2 matrix and evaluate targeting efficiency. Assuming that there is an agreement on the welfare indicator (such as per capita consumption), the most relevant cutoff has to be used, and may vary depending on the targeting method considered, making comparisons difficult (see below).[14]

The main welfare indicator used in this study is a per capita consumption aggregate.[15] The consumption aggregate is constructed by adding up household spending on different categories

[14] By the same token, the CGH index does not make meaningful comparisons between programs with different targets: CGH_{36} is appropriate for a targeting method selecting 35% of the households, but it does not make sense for another targeting method selecting 67% of the population. Also, the maximum value of CGH_{69} is 1.4 whereas it is 2.8 for CGH_{36}.

[15] While there is now a wide recognition that poverty is multidimensional by nature (Stoeffler et al. 2013, Sen 1999, Alkire and Foster 2011), we focus on consumption-based poverty in this paper for several reasons. Mostly, the PMT formula includes most of the variables which could be used to construct a multidimensional poverty (MDP) index, creating a strong overlap between the PMT and MDP. This would make the assessment based on this MDP index biased (because the PMT and the poverty measures would be constructed in a very similar way) and the comparison with community targeting “unfair”. Measures of MDP are used as robustness checks (see section 5.C).

of goods over the last year: i) "retrospective spending" collected for the last 3, 6 or 12 months on clothes, furniture, travels, ceremonies, etc.; ii) short-term spending (last 7 days) on and consumption of food and drinks (including self-produced food). Results remain robust when the consumption aggregate is constructed differently (excluding spending on health, funerals, etc.). They also remain robust when "*per consumption unit"* consumption is used rather than per capita consumption (i.e. employing a deflator which varies for each household member depending on its age and gender, rather than affecting a weight of 1 to each household member).

A household is defined as poor if its per capita consumption is below a given threshold that can be adjusted in several ways in order to obtain an appropriate poverty rate, to assess the efficiency of a given set of targeting methods. Indeed, community targeting was designed to target 70% of the villages population and actually targeted 67% of the households in the sample.[16] For that reason, a per capita threshold is used that identifies the poorest 67% of the households to assess community targeting efficiency. Similarly, hybrid (project) targeting includes 35% of the village population. Thus, when assessing hybrid targeting, the per capita consumption poverty threshold is adjusted so that 35% of the households are identified as poor. These two cases (community comparison and hybrid comparison) are illustrated in figure 1, where a global poverty threshold is used for all villages. This is the first scenario.

However, the percentage of eligible households targeted by the community varies by village. For that reason, it may be relevant to use per capita consumption (poverty) village thresholds rather than a global threshold. In this case, the poverty threshold is adjusted in each village in order to match community targeting rates (when assessing community targeting) or hybrid targeting rates

[16] 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.

(when assessing hybrid targeting). This second scenario is illustrated in figure 2 for two different villages.

Both global and village thresholds (scenarios 1 and 2) have different justifications. From a policy point of view, it may be interesting to understand community targeting efficiency in the project area, using a common definition of poverty (a single, global threshold). From an analytic point of view, it is important to understand community targeting efficiency separately from the project implementation gap (the fact that community targeting rates vary by village) and to define a different threshold in each village.[17]

The same applies to the PMT threshold employed, because PMT targeting provides with a household ranking (through PMT scores). Thus, unlike the community targeting threshold, the PMT threshold is fully adjustable in the analysis.[18] For that reason, PMT thresholds are adjusted in the exact same way the poverty threshold is adjusted. In scenario 1 (figure 1) PMT thresholds are chosen to select 67% of the households when we compare PMT to community targeting, and 35% of the households when PMT is compared with hybrid targeting. In scenario 2 (figure 2), PMT targeting is adjusted at the village level to match community targeting rates and hybrid targeting rates.

When comparing across targeting methods, we also compare 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

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

[18] The pilot project actually adjusted the PMT threshold to obtain 35% of the households as beneficiaries (hybrid targeting), after taking into account community targeting, rather than fixing in advance the PMT threshold.

methods can be regressive and perform worse than random selection). Universal targeting includes all households, so that exclusion errors do not exist. Finally, the alternative PMT formula employed is generated from the ECAM3 survey in a similar fashion to the PMT formula used in the pilot project, but with two distinct features: i) it is generated from observations in the Extreme-North region, which can be more 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.[19] 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 PMT and community targeting (when comparing PMT and community), or with PMT and hybrid targeting (when comparing PMT and hybrid targeting).[20]

B. Determinants of exclusion and drivers of community targeting

Beyond aggregate indicators of targeting efficiency, an important question (for policy reasons) is to identify characteristics associated with exclusion and inclusion errors to improve targeting mechanisms and reduce exclusion of poor households. Also, while the exact functioning of PMT targeting is known, the precise logic of community targeting is not apparent. Thus, understanding the general drivers of community targeting is useful to better capture the source of errors and/or

[19] The potential of regional and/or shorter PMT formulas is an important empirical question for practitioners, especially because in nationally representative surveys, the number of observations at the regional level limits the power of prediction from ex-ante assessments of targeting efficiency.

[20] Note that the poverty reduction of universal targeting with full household transfers (15,000 FCFA, the amount used in the project and to assess other targeting methods) 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) with universal targeting would be much higher, naturally, with full transfers.

discover the particular logic of community targeting (Alatas et al. 2012). To do so, we employ three different types of models.

The first type of models estimates, among poor households, the probabilities of being wrongly excluded by community and PMT targeting respectively. It only considers poor households to disentangle the probability of being selected (regardless of poverty status), of being poor (regardless of selection) and erroneously excluded (when poor) – since we are only interested in the latter effect here. A simple probit model studies the household characteristics associated with exclusion, where for household i exclusion error is defined as $ee_i = 1$ when i is poor but i is not targeted by mechanism j (community or PMT). The model is:

$$\mathrm{E}\left(ee_{ij} = 1 | \mathbf{X}_i\right) = \Phi\left(\boldsymbol{\beta}_j \mathbf{X}_i + \varepsilon_{ij}\right), \quad i \in P \tag{2}$$

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. $\mathbf{X}_i$ can include 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 (in terms of per capita consumption or in terms of PMT score). The global threshold (scenario 1) is used in this specification to better compare community and PMT targeting.

Similarly, we also study household characteristics associated with 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:

$$\Pr\left(e_{ij} = 1 | \mathbf{X}_i\right) = \Phi\left(\boldsymbol{\beta}_j \mathbf{X}_i + \varepsilon_{ij}\right), \quad i \in NP \tag{3}$$

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

[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*

The second model analyzes the drivers of community targeting and is run for all poor and non-poor households. Similarly to the previous model, it estimates how household characteristics are associated with being defined as "poor" (selected) by the community, with $s_i = 1$ when household i is selected by the community:

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

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

The third model is a multinomial logit model that studies specifically characteristics associated with mismatch between community and PMT targeting, in order to better identify households with different outcomes under the two targeting mechanisms. It considers 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 base category is being selected by community and PMT targeting (i), consequently the coefficients indicates a departure from having the two targeting methods agreeing that a household is poor. For household i, $t_i = j$ when i's targeting status is assigned to j, and $j = 1,2,3,4$ (one of the four categories described above):

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

(increase exclusion errors and reduce inclusion errors), or actually improve targeting efficiency (reduce both types of errors).

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

In all three models, errors are clustered at the village level to take into account the fact that each village targeting committee can introduce its own effect and because of other village effects. Results of the three models are used to discuss the specificities of PMT and community targeting mechanisms, and explore means to improve targeting efficiency for social assistance programs.

5. Results

A. Targeting assessment

Table 3 provides a comparison of community and PMT targeting by providing inclusion and exclusion errors as well as, Targeting Differential (TD), CGH index (CGH_{69}) and simulated poverty reduction measures. The PMT and per capita poverty thresholds used identify 67% of the households as poor (similarly to community targeting) at the global level (see section 4). Results indicate a poor performance of community targeting *per se*, since inclusion and exclusion errors are particularly high: 25.9% and 47.0% overall; which is higher than even random targeting. The targeting differential 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 the level of random targeting. The PMT targeting performs better, with lower exclusion errors (16.7%) and inclusion errors (21.0%). TD and CGH index (0.163 and 1. 094respectively) however show that poor households benefit only a little bit 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, which is higher than all other alternatives (except perfect targeting). The alternative PMT formula performs slightly worse than the project PMT formula, suggesting that using a reduced, regional formula would not improve targeting efficiency.

However, when one considers the simulated impact of the cash transfers on poverty, the differences between targeting methods is not as striking. Community targeting does not perform as well as other methods but still reduces poverty headcount by 13.5 percentage points. PMT targeting reduces poverty headcount by 0.191 (compared to 17.7 for random targeting) and poverty severity by 0.0756, which is not relatively close from perfect targeting (0.0918). Thus, PMT poverty headcount reduction is better than for universal targeting (0.169) but they perform similarly in terms of poverty severity reduction (0.0717 for universal targeting). There is not real difference between the PMT and the alternative PMT targeting methods.

When the threshold is fixed at the village level (see section 4), 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 4).[22] Again, community targeting does not perform clearly better than random targeting, especially in terms of poverty reduction where random targeting has a greater simulated impact. Here too, PMT targeting outperforms community targeting (and random targeting) under all the metrics used. Inclusion and exclusion errors are still low (20.6% and 17.3%) and TD 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, but TD_2 is higher for universal targeting. Also, interestingly here, 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.

[22] Because the definition of poverty is different with global or village thresholds, results of Table 3 and Table 4 are not comparable. Each table assesses and compares PMT and community targeting in a different manner.

Table 5 compares the hybrid targeting method used in the project (to select beneficiaries of the SSNPP) with PMT targeting, using the same indicators employed in Table 3: exclusion errors, Targeting Differential (TD), CGH index (CGH_{36}) and simulated poverty reduction. Here, the per capita poverty threshold is adjusted to include the 35% poorest households globally (i.e. the share of beneficiaries: see section 4). Hybrid and PMT targeting perform similarly for inclusion errors (51.1% and 51.6%) but hybrid exclusion errors (59.5%) are much higher than PMT targeting exclusion errors (44.7%).[23] Both methods clearly outperform random targeting. PMT targeting has a higher TD (0.142) and CGH index (1.277) as well, but its overall performance is not very impressive. In terms of TD_1 and TD_2, PMT outperforms hybrid targeting, but 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 greater for PMT targeting alone compared to hybrid targeting. 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 6), PMT targeting 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.

A gap between targeting efficiency ex-ante simulations and ex-post assessment is to be expected, for several reasons including: i) the time elapse between the PMT design dataset (2007) and the

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

PMT application assessment (2013); ii) the fact that Soulédé-Roua households are much poorer than those used for the design of the PMT formula on average. However, precautions were employed to ensure comparability between ex-ante and ex-post measurements (see section 3). When targeting chronic poor households (51.6% of the targeted areas population) with the PMT formula, inclusion and exclusion errors were found between 20% and 25% (depending on the specification) in ex-ante simulations (Nguetse-Tegoum and Stoeffler 2012). In Soulédé-Roua, PMT inclusion and exclusion errors are about 21% and 17% when using the community (67%) selection threshold. However, they rise to about 40-50% when the hybrid (35%) threshold is used. Thus, most of the difference between ex-ante and ex-post assessments seems to be due to the change of threshold, rather than to the project efficiency. Indeed, the potential of PMT targeting appears to decrease quickly when the level of coverage falls, one of the drawbacks of PMT targeting noted by Kidd and Wylde (2011).

Beyond these single indices which are mostly based on binary indicators (poor/non-poor, excluded/included), one can compare the distribution of the welfare indicator (per capita consumption aggregate) across targeting groups with non-parametric kernel densities. The distribution of households targeted by the community is not clearly different from the distribution of all households, and the two distributions intersect more than once (Figure 3). PMT targeted households' distribution is slightly on the left to the distribution of all households, which means that they are poorer – but the difference between the two distributions is very small, which is partly due to the fact that most households (67%) are targeted here. Overall, the PMT distribution does not clearly dominate the community distribution. When comparing densities of community targeted and non-targeted households (Figure 4), again the distributions intersect more than once, but community seem efficient at including more of the poorest households (on the left of the distribution). Here, PMT targeted households are clearly poorer than non-PMT targeted households (the distribution of PMT targeted households lies on the left). 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 (p-value = 0.000). However, a Kolmogorov-Smirnov fails to reject the null hypothesis for community and non-community selected households (p-value = 0.110). The per capita consumption cumulative density functions (CdF) for community vs. non-community selected households also confirms that the community is efficient at including the poorest households (on the left of the CdF), but also includes households which are less poor than those not selected by the community (on the right of the CdF) (Figure 5).

The same patterns are confirmed by the comparison of hybrid (project) targeted and non-targeted households (Figure 6).The hybrid targeted distribution is on the left of the hybrid non-targeted distribution, but the difference between PMT targeted and non-targeted distributions is clearer, showing that PMT targeting discriminates more between poor and non-poor households. Hybrid targeting includes slightly poorer households, but also richer ones, resulting in a slightly flatter distribution. Here, Kolmogorov-Smirnov tests reject the null hypothesis of equality of distributions both for hybrid vs. non-hybrid households and for PMT vs non-PMT selected households (p-value = 0.000 in both cases). This is confirmed by the CdF of hybrid vs. non-hybrid selected households and PMT vs non-PMT selected households (Figure 7). Hybrid selected households are clearly poorer than non-beneficiaries, but PMT targeting discriminates even more between selected and non-selected households.

These non-parametric densities confirm the results obtained for exclusion and inclusion errors, TD, CGH index and poverty reduction simulations. However, they also show that community targeting is slightly more efficient in including the poorest households (on the left tail of the distribution), and its poor performance is due to the inclusion of more households on the right tail of the distribution.

B. Characteristics of excluded households & drivers of community choice

To gain insight regarding the causes of the high rate of inclusion and exclusion errors identified above, the beginning of this sub-section (Tables 7 and 8) explores specifically the characteristics of households associated with targeting errors where poverty is still defined in terms of per capita consumption, as in the previous sub-section. That analysis also contributes to identify community selection motives. The end of the section focuses on the particular drivers of community selection as a departure from poverty conceived in strict per capita consumption terms.

Table 7 presents the determinants for a poor household of being (erroneously) not selected by two targeting methods. The first and second columns estimate the probability of community and PMT erroneous exclusion without controls for actual per capita consumption. Third and fourth columns include controls for actual per capita consumption, and column five controls for PMT scores (for community targeting only).[24] All estimations are done with probit models (see section 4). Results indicate that some characteristics are clearly associated with erroneous exclusion from community targeting: primary education, number of cows, owning a bicycle and having no solid walls. 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 community 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

[24] For PMT targeting, PMT scores alone predict selection perfectly and consequently cannot be used as controls.

decisions based on these very basic assets however, leads to errors in terms of per capita consumption poverty. The fact that association members have a lower risk of being excluded perhaps means that the wealth status of active members of the community is easier to know – and thus to rightly identify these members as poor.[25] Also, the community has a lower probability of excluding households which evaluate themselves as poor, suggesting that its decisions match local perception of poverty– but the probability of erroneous exclusion increase for households which declare themselves unable to meet their needs without falling into debt. Finally, per capita consumption (when included in the specification) also increases the risk of exclusion errors, suggesting that community targeting is more efficient among the poorest households (consistent with kernel densities). The positive and significant coefficient on PMT score in column (5) indicates that PMT 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 between the two methods.

The probability of exclusion errors on the other hand increases in PMT targeting for Christians and Animists (which represent the large majority of the population), polygamists and widows. The probability of exclusion errors is lower for households with primary and secondary education, households with a wasting child or a handicapped member, female and old household heads, large households[26], and households with no assets, no solid walls or no solid roof. Several of these variables are included in the PMT formula, which explain that they decrease exclusion errors (they increase the probability of inclusion among the poor). Interestingly, community and

[25] This is unlikely to indicate elite capture as association membership does not increase inclusion errors (see below).

[26] One of the reasons for the larger exclusion errors from community targeting compared to PMT targeting is that the community tends to select smaller households. Thus, when counted in terms of individuals, community exclusion errors of larger households are greater than exclusion errors of smaller households from the PMT. However, community errors are always larger than PMT errors, even when counted in terms of households (not individuals) and regardless of the weighting used.

PMT determinants never influence exclusion errors in the same direction, which suggest a potential for complementarities, even though in practice PMT targeting alone performs better than hybrid targeting in the SSNPP.

Determinants of inclusion errors also shed light on the exclusion errors determinants (Table 8). It appears that primary education does not only reduce exclusion errors from the PMT targeting, it also increases inclusion errors. This means 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 – leading to inclusion errors from the PMT formula. 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) also reduce errors of inclusion, meaning that they lead to greater exclusion regardless of actual poverty status. However, other variables reduces 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 meet ends. 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 also fails to take into account credit taken by households, which 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. In addition, some of these additional variables are difficult to measure accurately (value of assets) which makes their inclusion in a PMT formula costly (in terms of data collection) and/or increase the risk of targeting inaccuracy (if they are not well measured).

For community targeting, 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 also too likely to include households with self-evaluated bad health[27], who were also less likely to be excluded, indicating that the community considers this variable as important regardless of consumption status. If this is true, these “targeting errors” may be due to a different conception of poverty rather than a lack of information, targeting committees inefficiency and/or elite capture. To explore this hypothesis, the rest of this section considers in detail the particular drivers of community targeting.

Table 9 presents the drivers of community 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) or controlling for per capita consumption (column 2), PMT score (column 3) or both (column 4). The probability of community selection decreases with several variables: primary education, household size, number of cows, owning of a bicycle. The probability of selection also decreases with other variables which are usually associated with poverty: having a wasting child in the household, no solid walls, and needing to go into debt to

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

meet ends. On the other hand, the probability of selection increases with variables which may be 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, to include longer-term determinants of vulnerability and poverty. Indeed, the community tends to focus on households with limited income-generating potential, such as older, isolated households with low human and physical capital. 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 indicates a divergence between the two targeting methods, which is now further analyzed.

A multinomial logit model (see section 4) is used to identify variables associated with being selected by the PMT only (column 1), by the community only (column 2), or by neither (column 3), compared to the baseline category, being selected by both PMT and community targeting (Table 10).[28] Variables which increase the probability of being selected only by the PMT are those included in the PMT formula such as household size, owning a bicycle, having no solid walls. However, the 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, being a widow, borrowing land. Having secondary education, household

[28] Several tests of Independence of Irrelevant Alternatives (IIA) were performed: Hausman tests, suest-based Hausman tests and Small-Hsiao tests, on Table 10 specification as well as on alternative specifications (excluding the category “neither” or changing the base category). All tests resulted in failure 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 hold (Long and Freese 2006, 244-5).

size, having no solid walls, solid roof or toilets decrease the probability of being selected by the community only (compared to being selected by PMT and community). Also, being a member of an association decrease the probability of being selected by PMT only or by community only. Having no agricultural tools, being a female household head, age of the household head or being self-evaluated as very poor decrease the probability to be selected by neither PMT nor community. On the other hand having a wasting child in the household, owning a micro-enterprise, or needing to go into debt to meet ends increase this probability of being selected by none of the targeting methods. 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 the community and the PMT. Some deprivations are only taken into account by the community, such as being a widow, but in general, households with a given deprivation have a greater probability of being selected by both targeting methods. Overall, and consistent with findings from other countries (Alatas et al. 2012, Pop 2014), these regression results suggest that community targeting uses different criteria than PMT targeting and do not focus on low per capita consumption and its correlates (house material, etc.). Rather, communities 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.).

C. Alternative assessments of community targeting

Because communities seem to employ different criteria in their selection of poor households rather than per capita consumption only, an evaluation of community targeting under different definitions of poverty is necessary. Indeed, the fact that communities follow a different definition of poverty does not mean that community targeting is efficient in identifying poor households under its own criteria. In this sub-section, three different strategies are used to assess community targeting and compare it to other targeting methods.

First, community targeting efficiency to select the most food insecure households is assessed. A Household Food Insecurity Access Scale (HFIAS) score is constructed following Coates, Swindale and Bilinsky (2007). As done previously with poverty defined as per capita consumption, the 67% households with the highest HFIAS scores are defined as poor (food insecure) in order to obtain as many households which are food insecure, selected by the community, and selected by the PMT in each village (see section 4). Errors of inclusion and exclusion are computed as before.

Second, community targeting efficiency to select multidimensionally poor households is assessed. A multidimensional poverty (MDP) index is constructed following the counting approach, which means counting dimensions in which each household is deprived (Alkire and Foster 2011). The dimensions considered are health, education, nutrition and food security, living standards, physical assets, vulnerability and self-evaluated poverty status.[29] Again, households with the highest MDP index are defined as poor so the same number of households are multidimensionally poor, are selected by the community, and are selected by the PMT in each village. Errors of inclusion and exclusion are computed.

Third, the efficiency of the community to select households which are predicted as poor according to community selection criteria is assessed. Doing so is similar to what was done when creating a PMT formula from the ECAM 3 dataset: the sample is randomly split and the first part (2/3 of the sample) is used to predict community selection using a simple probit model. Using the same variables and the weights obtained from the model, community selection is predicted for the second part (1/3 of the sample). Households with the highest predicted probability of

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

being selected by the community in each village are defined as “community poor” households so that 67% of them are considered as “community poor”. Then, the efficiency of the community to select households corresponding to its own criteria is assessed by computing errors of inclusion and exclusion in the usual manner. This simulation is run 300 times, and average errors of inclusion and exclusion are computed.

Results from these three methods to assess community efficiency still show high levels of errors from community targeting (Table 11). Community targeting errors of inclusion are moderate: 26.4% for food insecurity and 27.3% for MDP, which is lower than with PMT targeting (31.7% and 34.4% respectively). However, errors of exclusion are even higher: 38.1% for food insecurity and 35.6% for MDP, which is much higher than PMT errors and also random targeting. When considering “community poor” households (those predicted to be selecting by the community), errors are still as high as for per capita consumption poor households: 22.6% of inclusion errors and 41.2% exclusion errors. These analyses illustrate the fact 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, since communities do not select households which are seemingly similar. The results contribute to cast doubt on the capacity of the community, in Soulédé-Roua, to select poor households in a consistent manner, regardless of the poverty criteria employed.

6. Conclusion and policy recommendations

This article studies the efficiency of two targeting mechanisms (community and PMT) employed in a small unconditional cash transfer pilot project in Northern Cameroon. Its findings are not generalizable to all poverty alleviation programs using this type of targeting methods, but are informative regarding the potential of targeting methods in actual projects implemented in extremely poor, rural, Sub-Saharan environments. Results are not very encouraging for community targeting when per capita consumption is used to define poverty. Community targeting indeed performs worse than PMT targeting according to all the indicators and for all thresholds used – and also worse than random targeting. Our results differ from Alatas et al. (2012) in that in Soulédé-Roua, transfers based on community targeting have a significantly lower simulated impact on poverty compared to transfers delivered by PMT targeting. Our results also question the efficiency of PMT targeting, whose exclusion and inclusion errors are above 40% (at the selection threshold used in the project) and whose simulated impact on poverty reduction is not clearly higher than the simulated impact of universal transfers with equal budget.

The analysis of the determinants of targeting errors suggests that the PMT formula is slightly disconnected from the local context, which is poorer than the national context on which the formula is based. While this implies potential gains from a local or regional formula, such a formula (based on national statistics used at the regional level) does not perform better when tested in this application. Poor performance of the regional PMT may mean that there would be gains in terms of targeting efficiency from collecting original, regional, recent data to design PMT formulas adapted to the local environment.

Similarly to previous findings, it seems that the community has a different conception of poverty that simply being below a per capita consumption threshold. In Soulédé-Roua, community targeting focuses on vulnerable households with limited income potential because of obvious lack of human or physical capital. However, some of the characteristics associated with a reduction of exclusion errors (such as being member of an association) suggest that there is also a lack of information which leads to deceptive community targeting efficiency. This hypothesis was further tested by considering targeting efficiency of CBT using different methods and definitions of poverty. These tests also resulted in high targeting errors for CBT, suggesting that community targeting produces very variable outcomes on observationally similar households. Thus, CBT targeting results are not only explained by the fact that communities use a different selection criteria (rather than per capita consumption only), but also that communities lack clear and consistent targeting criteria.

Because variables associated with higher probabilities of errors of inclusion and exclusion differ greatly, there may exist potential complementarities between PMT and community targeting, which could be exploited to increase targeting efficiency. These complementarities do not translate into a finer targeting in Soulédé-Roua, where hybrid targeting does not improve performance compared to PMT targeting only, because community targeting *per se* was inefficient in selecting per capita consumption-poor households. However, many variables associated with community selection are arguably components of multidimensional poverty and determinants of chronic poverty (low human and physical capital).

The poor performance of community targeting in terms of per capita consumption and the implementation gap noticed in the pilot project regarding community targeting rates per village suggest two main policy recommendations. First, if community targeting performance is not improved, social safety nets programs should weight the cost implied by a lower targeting efficiency (in terms of poverty defined by per capita consumption) with the gains in terms of satisfaction and project efficiency which are expected from the involvement of the community. Second, efforts have to be made to improve community targeting performance by providing guidance, setting-up clear objectives and definitions of poverty (consistent with the policy objective and local perception), and enforcing the rules of the program. As noted, targeting efficiency depends on well-designed methods as much as on good implementation (Coady, Grosh, and Hoddinott 2004). Possible means for improving the work of community targeting committees include household visits and wealth household ranking (rather than only separating poor from non-poor), as well as respecting village selection rates targets.

Areas for further research are related to these policy objectives. First, the gain (or loss) in satisfaction from community targeting has to be further studied, in order to be able to weight targeting efficiency and other objectives. For instance, it is well recognized that community involvement has several advantages for successful program implementation, but these advantages have to be measured and compared to the disadvantage of higher targeting errors. Second, it is necessary to develop indicators of targeting efficiency which are related the targeting criteria used by the community to select poor households. Only when households will be clearly defined as poor under these criteria by the researcher, it will be possible to disentangle poor targeting efficiency (because of capture elite, lack of information, tiredness of the targeting committee members or any other reason) from differences in definition of poor households. Finally, beyond targeting *per se*, it would be important to study the impact of targeting methods on program success regarding its primary goals, for instance in unconditional cash transfer projects (UCT), improved nutrition of beneficiaries or investments in productive activities. For UCTs, it may be possible to observe a positive impact of transfers on beneficiaries in a Sahelian context even in the absence of perfect targeting (Stoeffler and Mills 2014). Promising results for beneficiaries at the aggregate level does not mean, however, that efficient targeting is unimportant. There will be negative effects associated with exclusion both at the individual level and at the aggregate level, which is why more investments in targeting systems are needed (Del Ninno and Mills 2014). The rapid spread of targeting systems for social safety nets in Sub-

Saharan Africa, aimed at selecting millions of beneficiaries in dozens of countries, generates a critical need for further research efforts in this area.

References

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

Ahmed, A.U., and H.E. Bouis. 2002. "Weighing what's practical: proxy means tests for targeting food subsidies in Egypt." *Food Policy* no. 27 (5-6):519-540.

Alatas, V., A. Banerjee, R. Hanna, B.A. Olken, and J. Tobias. 2012. "Targeting the poor: Evidence from a field experiment in indonesia." *The American Economic Review* no. 102 (4):1206-1240.

Alderman, Harold. 2002. "Do local officials know something we don't? Decentralization of targeted transfers in Albania." *Journal of Public Economics* no. 83 (3):375-404.

Alkire, Sabina, and James Foster. 2011. "Counting and multidimensional poverty measurement." *Journal of Public Economics* no. 95 (7):476-487.

Banerjee, Abhijit, Esther Duflo, Raghabendra Chattopadhyay, and Jeremy Shapiro. 2007. Targeting Efficiency: How well can we identify the poor? edited by IFMR working paper.

Besley, T., and S.M.R. Kanbur. 1990. *The principles of targeting*. Vol. 385: Office of the Vice President, Development Economics, World Bank.

Bourguignon, F., F.H.G. Ferreira, and P.G. Leite. 2003. "Conditional cash transfers, schooling, and child labor: micro-simulating Brazil's Bolsa Escola program." *The World Bank Economic Review* no. 17 (2):229-254.

Cameron, Lisa, and Manisha Shah. 2014. "Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia." *Economic Development and Cultural Change* no. 62 (2):381-415.

Coady, D., M.E. Grosh, and J. Hoddinott. 2004. *Targeting of transfers in developing countries: Review of lessons and experience*: World Bank Publications.

Coates, Jennifer, Anne Swindale, and Paula Bilinsky. 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, Jonathan, and Michael Kevane. 2002. "Community-based targeting mechanisms for social safety nets: A critical review." *World Development* no. 30 (3):375-394.

Cornia, Giovanni Andrea, and Frances Stewart. 1993. "Two errors of targeting." *Journal of International Development* no. 5 (5):459-496.

Del Ninno, Carlo , and Bradford Mills. 2014. *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*. Washington DC: World Bank.

Ellis, Frank. 2012. "'We Are All Poor Here': Economic Difference, Social Divisiveness and Targeting Cash Transfers in Sub-Saharan Africa." *Journal of Development Studies* no. 48 (2):201-214.

Ferguson, James. 2013. "Declarations of dependence: labour, personhood, and welfare in southern Africa." *Journal of the Royal Anthropological Institute* no. 19 (2):223-242.

Foster, James, Joel Greer, and Erik Thorbecke. 1984. "A class of decomposable poverty measures." *Econometrica: Journal of the Econometric Society*:761-766.

Galasso, Emanuela, and Martin Ravallion. 2005. "Decentralized targeting of an antipoverty program." *Journal of Public economics* no. 89 (4):705-727.

Garcia, Marito, and Charity MT Moore. 2012. *The Cash Dividend: The Rise of Cash Transfer Programs in Sub-Saharan Africa*. Washington, DC: The World Bank.
Groover, K.D. 2014. "Climatic Shocks and Poverty Dynamics in Mozambique." In *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*, edited by Carlo del Ninno and Bradford Mills. Washington, DC: World Bank.
Grosh, M.E., C. Del Ninno, E.D. Tesliuc, and A. Ouerghi. 2008. *For protection and promotion: The design and implementation of effective safety nets*: World Bank.
Grosh, Margaret E, and Judy L Baker. 1995. Proxy means tests for targeting social programs: Simulations and speculation. World Bank (Washington, DC).
Handa, Sudhanshu, Carolyn Huang, Nicola Hypher, Clarissa Teixeira, Fabio V Soares, and Benjamin Davis. 2012. "Targeting effectiveness of social cash transfer programmes in three African countries." *Journal of development effectiveness* no. 4 (1):78-108.
Karlan, Dean, and Bram Thuysbaert. 2013. Targeting ultra-poor households in Honduras and Peru. National Bureau of Economic Research.
Kidd, S., and E. Wylde. 2011. "Targeting the Poorest: An assessment of the proxy means test methodology." *AusAID Research Paper, Australian Agency for International Development, Canberra, Australia*.
Leite, P., Q. Stoeffler, and A. Kryeziu. 2013. "Targeting Effectiveness of Social Safety Net Programs in Senegal." In *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*, edited by Carlo del Ninno and Bradford Mills. Washington, DC: World Bank.
Long, J Scott, and Jeremy Freese. 2006. *Regression models for categorical dependent variables using Stata*: Stata press.
Maluccio, John A. 2009. "Household targeting in practice: the Nicaraguan Red de Protección Social." *Journal of International Development* no. 21 (1):1-23.
Mansuri, Ghazala, and Vijayendra Rao. 2004. "Community-based and-driven development: A critical review." *The World Bank Research Observer* no. 19 (1):1-39.
Mkandawire, T. 2005. *Targeting and universalism in poverty reduction*: United Nations Research Institute for Social Development.
Monchuk, Victoria. 2013. *Reducing Poverty and Investing in People: The New Role of Safety Nets in Africa*: World Bank Publications.
Narayan, A., and N. Yoshida. 2005. "Proxy Means Tests for Targeting Welfare Benefits in Sri Lanka." *Report No. SASPR–7, Washington, DC: World Bank, http://siteresources. worldbank. org/EXTSAREGTOPPOVRED/Resources/49344 0-1102216396155/572861-1102221461685/Proxy+ Means+ Test+ for+ Targeting+ Welfare+ Benefits. pdf, accessed February* no. 5:2009.
Nguetse-Tegoum, Pierre, and Quentin Stoeffler. 2012. Programme de transferts monétaires sociaux: le ciblage des pauvres chroniques. World Bank.
Niehaus, Paul, and Antonia Atanassova. 2013. "Targeting with agents." *American Economic Journal: Economic Policy* no. 5 (1):206-238.
Olivier de Sardan, Jean-Pierre. 2013. Les transferts monétaires au Niger : la manne et les soupçons. Niamey: LASDEL.
Pop, L. 2014. "Options for Targeting of Safety Nets in Ghana." In *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*, edited by Carlo del Ninno and Bradford Mills. Washington, DC: World Bank.
Ravallion, M. 2009. "How relevant is targeting to the success of an antipoverty program?" *The World Bank Research Observer* no. 24 (2):205-231.

Sabates-Wheeler, Rachel, Alex Hurrell, and Stephen Devereux. 2014. Targeting social transfer programmes: Comparing design and implementation errors across alternative mechanisms. WIDER Working Paper.

Schüring, Esther. 2014. "Preferences for Community-based Targeting-Field Experimental Evidence from Zambia." *World Development* no. 54:360-373.

Sen, Amartya. 1995. "The political economy of targeting." In *Public Spending and the Poor*, edited by Dominique Van de Walle and Kimberly Nead. Washington, D.C.: World Bank.

Sen, Amartya. 1999. *Development as freedom*: Oxford University Press.

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

Slater, Rachel, John Farrington, M Vigneri, M Samson, and S Akter. 2009. "Targeting of Social Transfers: A review for DFID." *London: ODI*.

Stoeffler, Q. 2013. "The Impact of Unconditional Cash Transfer Programs on Farmers: Evidence From Ex-ante Simulations." *Public Knowledge Journal* no. 4 (2).

Stoeffler, Q., J. Alwang, B. Mills, and N. Taruvinga. 2013. Multidimensional Poverty in Crisis: Lessons from Zimbabwe.

Stoeffler, Q., P. Nguetse-Tegoum, and B. Mills. 2013. "Generating a System for Targeting Unconditional Cash Transfers in Cameroun." In *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*, edited by Carlo del Ninno and Bradford Mills. Washington, DC: World Bank.

Stoeffler, Quentin, and Bradford Mills. 2014. "Households' investments in durable and productive assets in Niger: quasi-experimental evidences from a cash transfer project."

Van de Walle, D., and K. Nead. 1995. *Public spending and the poor*. Edited by The Wold Bank. Baltimore: Johns Hopkins University Press.

World Bank. 2011a. Cameroon: Social Safety Nets

World Bank. 2011b. Social Safety Net Programs in Cameroon: A Feasibility Study

Tables

Table 1: Descriptive Statistics

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

This household owns land	0.667	0.629	0.680	0.634
Total land surface	8845.8	9604.0	9290.0	11606.7
This household borrows land	0.509	0.507	0.510	0.534
Grows cotton	0.394	0.381	0.427	0.446
Grows rice	0.135	0.134	0.137	0.146
Household grows maize	0.496	0.491	0.520	0.527
Hired labor	0.101	0.0925	0.0930	0.0905
Household owns no agricultural tools	0.0514	0.0613	0.0486	0.0546
Household bought (paid) fertilizer	0.435	0.416	0.459	0.477
Value of agricultural sales	75.39	101.7	88.36	146.0
Has Micro-enterprise	0.255	0.224	0.257	0.235
Micro-enterprise profits (if has ME)	43.33	33.57	43.88	40.50
Micro-enterprise equipment value (FCFA)	17.49	22.45	14.23	7.250
Some assistance available (any type)	0.777	0.772	0.772	0.748
Types of assistance (#)	1.731	1.745	1.722	1.702
Value assets (FCFA)	46.89	52.52	50.56	73.39
Types of assets (#)	0.504	0.510	0.495	0.560
No assets	0.710	0.713	0.712	0.701
Household asset index	0.333	0.318	0.327	0.356
The household owns at least 1 bicycle	0.0649	0.0501	0.0725	0.0637
Low Household Hunger Score	0.433	0.418	0.428	0.415
Moderate Household Hunger Score	0.389	0.398	0.387	0.388
Sever hunger (HHS)	0.178	0.184	0.185	0.197
Household Food Insecurity Access Scale (score)	12.06	12.33	12.07	12.35
Household Dietary Diversity Score	6.333	6.256	6.369	6.353
No solid walls	0.873	0.848	0.887	0.868
No solid roof	0.911	0.919	0.917	0.922
No toilets	0.0742	0.0735	0.0682	0.0759
Wasting child in the household	0.0674	0.0528	0.0763	0.0565
Stunting child in the household	0.157	0.141	0.168	0.149
Self-evaluated very poor	0.468	0.518	0.456	0.504
Needs to go into debt	0.541	0.516	0.548	0.541
Observations	1723	1163	1163	598

Descriptive Statistics for households in Soulede-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 2: Targeting matrix

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

Table 3: 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	-0.135	-0.191	-0.188	-0.263	-0.177	-0.169
FGT_1 reduction	-0.0883	-0.129	-0.125	-0.160	-0.108	-0.118
FGT_2 reduction	-0.0531	-0.0756	-0.0736	-0.0918	-0.0608	-0.0717

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 4: 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	-0.108	-0.146	-0.138	-0.233	-0.125	-0.162
FGT_1 reduction	-0.0793	-0.111	-0.107	-0.136	-0.0933	-0.100
FGT_2 reduction	-0.0544	-0.0733	-0.0716	-0.0840	-0.0626	-0.0640

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

Table 5: 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	-0.106	-0.136	-0.126	-0.278	-0.0954	-0.109
FGT_1 reduction	-0.0380	-0.0480	-0.0462	-0.0908	-0.0301	-0.0454
FGT_2 reduction	-0.0171	-0.0210	-0.0202	-0.0388	-0.0123	-0.0220

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

Table 6: 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	-0.0988	-0.119	-0.118	-0.258	-0.0843	-0.113
FGT_1 reduction	-0.0358	-0.0467	-0.0420	-0.0811	-0.0279	-0.0402
FGT_2 reduction	-0.0160	-0.0214	-0.0191	-0.0346	-0.0125	-0.0191

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

Table 7: Determinants of Exclusion Errors

	(1) Community exclusion error	(2) PMT exclusion error	(3) Community exclusion error	(4) PMT exclusion error	(5) Community exclusion error
Primary education	**0.241***	**-0.613*****	0.219	**-0.595*****	0.200
	(1.65)	**(-4.98)**	(1.46)	**(-4.78)**	(1.32)
Secondary 1 education	0.194	**-0.547*****	0.164	**-0.531*****	0.148
	(0.93)	**(-3.12)**	(0.77)	**(-2.98)**	(0.69)
Secondary 2 education	-0.060	0.233	-0.090	0.250	-0.087
	(-0.23)	(0.92)	(-0.34)	(0.95)	(-0.33)
Wasting child in the household	0.181	**-0.540***	0.184	**-0.533***	0.206
	(1.28)	**(-1.77)**	(1.36)	**(-1.74)**	(1.46)
Christian	-0.061	**0.358****	-0.061	**0.369****	-0.053
	(-0.47)	**(2.33)**	(-0.49)	**(2.52)**	(-0.40)
Animist	0.040	**0.279***	0.035	**0.285***	0.038
	(0.29)	**(1.74)**	(0.26)	**(1.86)**	(0.27)
Handicap	0.074	**-0.237***	0.099	**-0.260***	0.071
	(0.95)	**(-1.91)**	(1.31)	**(-1.96)**	(0.92)
Health not good (self-evaluation)	-0.135	0.023	-0.113	0.008	-0.130
	(-1.10)	(0.24)	(-0.93)	(0.08)	(-1.08)
Received shock on field	-0.116	0.003	-0.137	0.016	-0.121
	(-0.83)	(0.04)	(-1.04)	(0.18)	(-0.88)
Woman household head	-0.005	**-0.154***	-0.005	**-0.158***	0.012
	(-0.04)	**(-1.70)**	(-0.04)	**(-1.72)**	(0.09)
Polygamist	0.047	**0.264****	0.043	**0.270****	0.056
	(0.66)	**(2.20)**	(0.61)	**(2.18)**	(0.78)
Household head is widow	-0.078	**0.404***	-0.056	**0.401***	-0.058
	(-0.48)	**(1.89)**	(-0.34)	**(1.88)**	(-0.35)
Household size	0.034	**-0.410*****	**0.051***	**-0.430*****	-0.005
	(1.43)	**(-20.16)**	**(1.71)**	**(-14.43)**	(-0.13)
Household members between 15 and 59	**-0.112*****	0.085	**-0.117*****	0.092	**-0.104****
	(-2.58)	(1.44)	**(-2.58)**	(1.48)	**(-2.18)**
Age of the household head	-0.006	**-0.006****	-0.007	**-0.005***	-0.007
	(-1.22)	**(-2.32)**	(-1.38)	**(-1.91)**	(-1.46)
Household obtained credit	0.020	-0.109	0.013	-0.102	0.010
	(0.28)	(-0.97)	(0.22)	(-0.93)	(0.14)
Association member	**-0.397***	0.194	**-0.405****	0.188	**-0.382***
	(-1.93)	(0.79)	**(-2.01)**	(0.79)	**(-1.92)**
Number of cows	**0.236***	0.006	**0.232***	0.012	**0.251***
	(1.77)	(0.07)	**(1.75)**	(0.14)	**(1.90)**
Value of livestock sales	0.006	-0.014	0.005	-0.014	0.005
	(1.40)	(-1.41)	(1.27)	(-1.36)	(1.31)
This household borrows land	0.168	0.132	0.145	0.156	0.177
	(1.06)	(1.23)	(0.93)	(1.41)	(1.10)

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

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

Table 8: Determinants of Inclusion Errors

	(1) Community inclusion error	(2) PMT inclusion error	(3) Community inclusion error	(4) PMT inclusion error	(5) Community inclusion error
Primary education	-0.162	**0.410*****	-0.168	**0.387*****	-0.081
	(-1.06)	**(2.94)**	(-1.01)	**(2.88)**	(-0.52)
Secondary 1 education	-0.274	0.304	-0.279	0.291	-0.217
	(-1.50)	(1.45)	(-1.54)	(1.36)	(-1.14)
Secondary 2 education	-0.355	0.222	-0.360	0.224	-0.331
	(-1.51)	(0.60)	(-1.47)	(0.58)	(-1.37)
Wasting child in the household	-0.306	**-0.758****	-0.308	**-0.763****	-0.412
	(-1.05)	**(-2.37)**	(-1.05)	**(-2.46)**	(-1.55)
Christian	0.251	**-0.457***	0.252	**-0.450***	0.210
	(1.23)	**(-1.84)**	(1.26)	**(-1.80)**	(1.01)
Animist	0.131	-0.098	0.131	-0.107	0.134
	(0.65)	(-0.79)	(0.65)	(-0.83)	(0.67)
Handicap	0.022	0.107	0.022	0.101	0.068
	(0.15)	(0.98)	(0.15)	(0.93)	(0.45)
Health not good (self-evaluation)	**0.443*****	-0.050	**0.446*****	-0.040	**0.447*****
	(3.68)	(-0.29)	**(3.58)**	(-0.24)	**(4.10)**
Received shock on field	0.145	-0.200	0.148	-0.178	0.148
	(1.45)	(-1.29)	(1.42)	(-1.17)	(1.41)
Woman household head	**0.265***	0.007	**0.264***	0.005	**0.254***
	(1.75)	(0.05)	**(1.75)**	(0.04)	**(1.69)**
Polygamist	-0.077	**-0.226***	-0.077	**-0.213***	-0.087
	(-0.53)	**(-1.77)**	(-0.52)	**(-1.65)**	(-0.57)
Household head is widow	0.295	-0.072	0.294	-0.098	0.289
	(1.61)	(-0.30)	(1.59)	(-0.41)	(1.64)
Household size	**-0.085****	**0.539*****	**-0.088****	**0.493*****	**-0.000**
	(-2.01)	**(8.53)**	**(-2.25)**	**(6.25)**	**(-0.00)**
Household members between 15 and 59	**0.185****	-0.015	**0.186****	0.002	**0.182****
	(2.32)	(-0.14)	**(2.35)**	(0.02)	**(2.33)**
Age of the household head	**0.010***	0.001	**0.010***	0.001	**0.011****
	(1.84)	(0.25)	**(1.85)**	(0.36)	**(2.10)**
Household obtained credit	0.020	**0.391*****	0.017	**0.356*****	0.063
	(0.10)	**(3.04)**	(0.08)	**(2.79)**	(0.29)
Association member	0.086	0.266	0.086	0.273	0.078
	(0.43)	(0.98)	(0.44)	(1.01)	(0.38)
Number of cows	**-0.106***	-0.074	**-0.105***	-0.071	**-0.132***
	(-1.74)	(-0.70)	**(-1.73)**	(-0.67)	**(-1.79)**
Value of livestock sales	0.002	-0.009	0.002	-0.010	0.001
	(0.41)	(-0.86)	(0.41)	(-0.93)	(0.14)
This household borrows land	**-0.264***	-0.172	**-0.268***	-0.191	**-0.297***
	(-1.70)	(-0.73)	**(-1.75)**	(-0.81)	**(-1.88)**
This household does	**0.356*****	**-0.397****	**0.356*****	**-0.411****	**0.332*****

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

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

Table 9: Determinants of Community Selection

	(1) No control	(2) Control: PMT scores	(3) Control: pc consumption	(4) Control: PMT scores and pc consumption
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)**
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	**0.290*****	**0.295*****	**0.281*****	**0.286*****

not own land	**(3.60)**	**(3.84)**	**(3.35)**	**(3.58)**
Household bought	-0.127	-0.115	-0.119	-0.108
(paid) fertilizer	(-0.80)	(-0.74)	(-0.76)	(-0.70)
Household owns no	**0.328***	**0.323***	**0.337****	**0.332***
agricultural tools	**(1.91)**	**(1.83)**	**(2.01)**	**(1.93)**
Value of agricultural	0.000485	0.000520	0.000555	0.000589
sales	(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)
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	**-0.338****	**-0.329*****	**-0.332****	**-0.322****
least 1 bicycle	**(-2.50)**	**(-2.61)**	**(-2.45)**	**(-2.56)**
No solid walls	**-0.365****	**-0.325****	**-0.359****	**-0.319****
	(-2.16)	**(-2.03)**	**(-2.12)**	**(-1.99)**
No solid roof	0.146	0.203	0.139	0.195
	(1.24)	(1.60)	(1.17)	(1.55)
No toilets	-0.127	-0.0646	-0.122	-0.0602
	(-1.14)	(-0.59)	(-1.11)	(-0.55)
Household Dietary	-0.0159	-0.0167	-0.00463	-0.00569
Diversity Score	(-0.59)	(-0.62)	(-0.14)	(-0.17)
Self-evaluated very	**0.183***	**0.191***	**0.182***	**0.190***
poor	**(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			-0.0873	-0.0854
consumption			(-0.76)	(-0.75)
Constant	0.572	0.145	1.522	1.076
	(1.11)	(0.28)	(1.12)	(0.81)
Observations	1714	1714	1714	1714
Log-Likelihood	-994.6	-987.1	-993.8	-986.4

t statistics in parentheses

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

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

Table 10: Multinomial Logit model of determinants of mismatch between community and PMT targeting, village threshold

	Selected by the PMT, not the community	Selected by the community, not the PMT	Not selected by the PMT or the community
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)
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)**
Value assets (FCFA)	-0.000261	-0.0000563	**-0.0000625***
	(-0.36)	(-1.54)	**(-1.77)**
No assets	0.245	0.0239	0.00328
	(1.01)	(0.10)	(0.01)
The household owns at least 1 bicycle	**0.899*****	0.305	0.0652
	(3.29)	(0.62)	(0.15)
No solid walls	**0.557****	**-0.458****	0.548
	(2.32)	**(-2.18)**	(1.14)
No solid roof	-0.193	**-0.715*****	**-0.683****
	(-0.62)	**(-3.50)**	**(-2.00)**
No toilets	-0.0229	**-1.055****	-0.342
	(-0.07)	**(-2.27)**	(-1.42)
Household Dietary Diversity Score	-0.0224	-0.0711	0.0156
	(-0.56)	(-1.42)	(0.20)
Self-evaluated very poor	-0.106	-0.221	**-0.514****
	(-0.80)	(-0.91)	**(-1.98)**
Needs to go into debt	0.0802	0.0187	**0.497*****
	(1.00)	(0.11)	**(3.70)**
Constant	-1.179	3.382**	1.663
	(-1.13)	(2.50)	(0.92)
# of households	321	321	239
Observations	1657		
Log-Likelihood	-1765.8		

t statistics in parentheses
Multinomial Logit model of determinants of being selected by the PMT but not the community, and vice versa. Baseline category: selected by PMT and community. For comparison purposes, the PMT thresholds are adjusted in each village to obtain as many households which are targeted by the community and by the PMT. Observations: 1657 households.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Targeting Errors with Alternative Poverty Definitions

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

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

Figures

Figure 1: PMT and poverty thresholds adjusted to match Community targeting and Hybrid (project) targeting rates (global threshold)

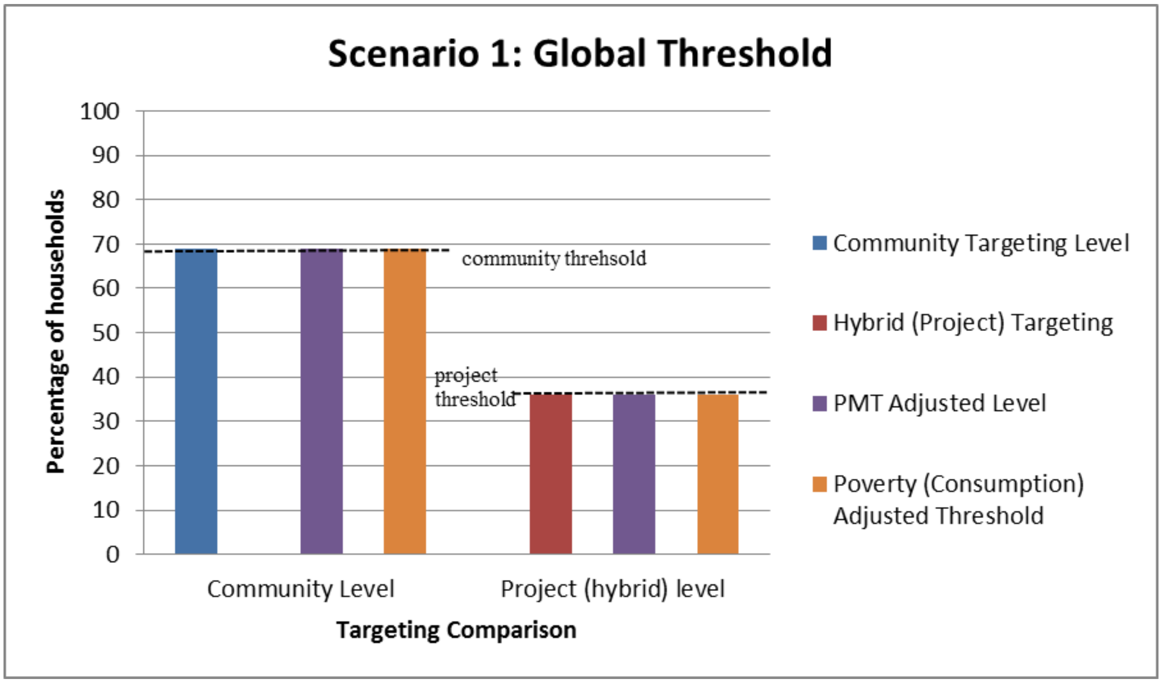


Figure 2: PMT and poverty thresholds adjusted to match Community targeting and Hybrid (project) targeting percentage of the households selected (village threshold)

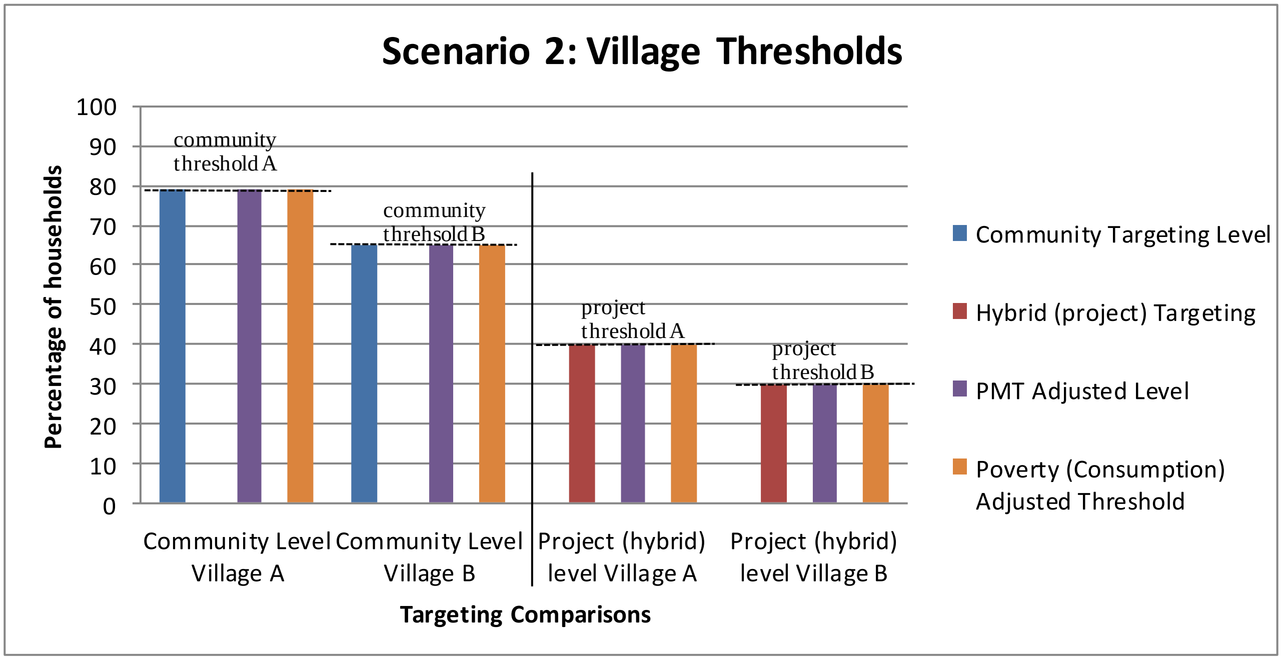
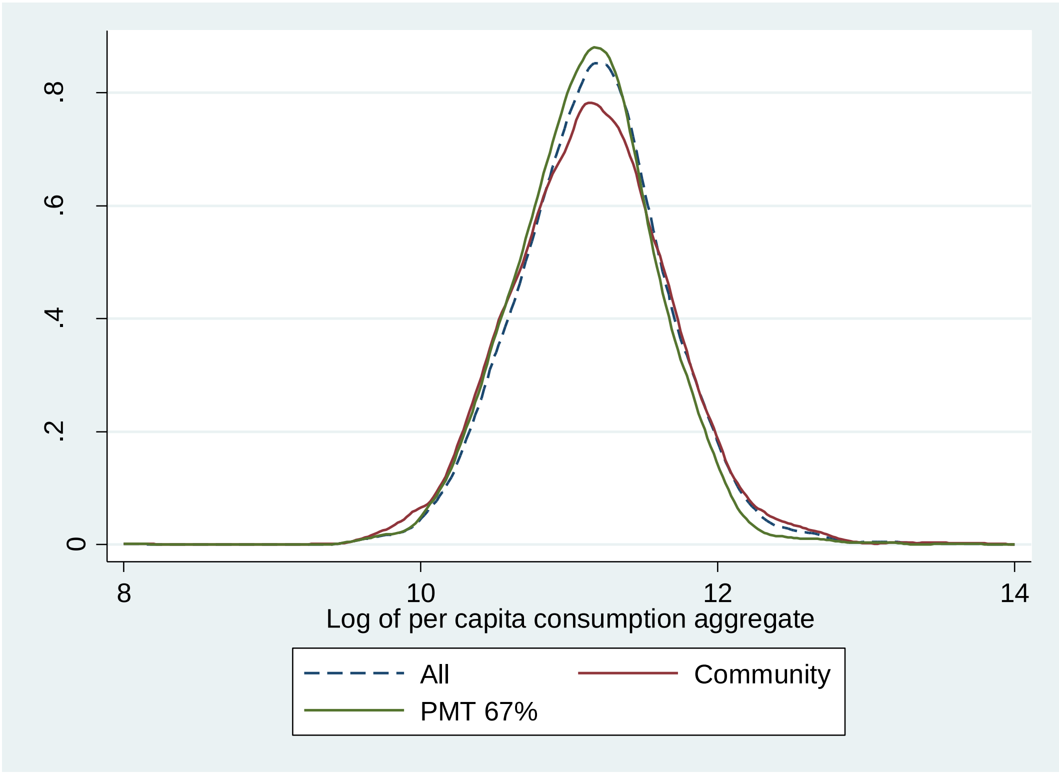
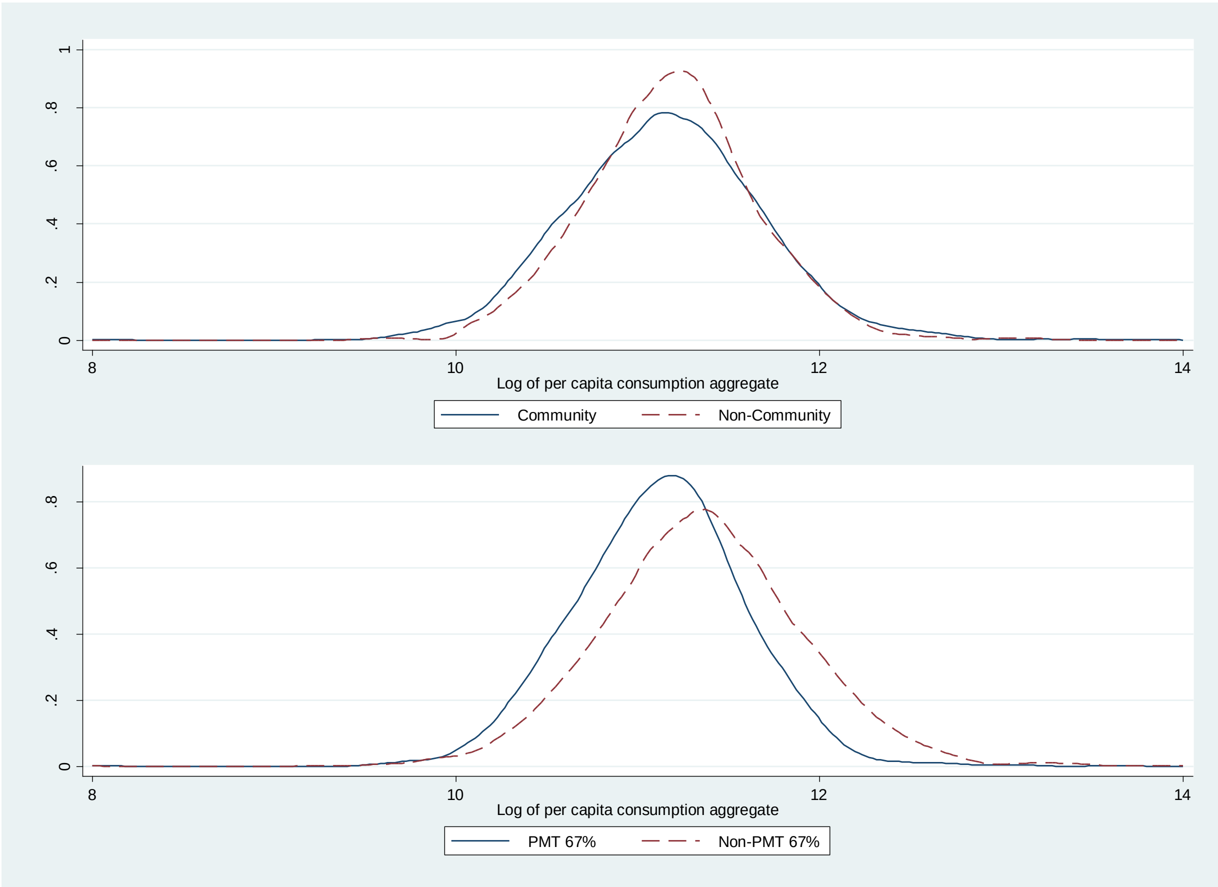


Figure 3: Per capita consumption by targeting group



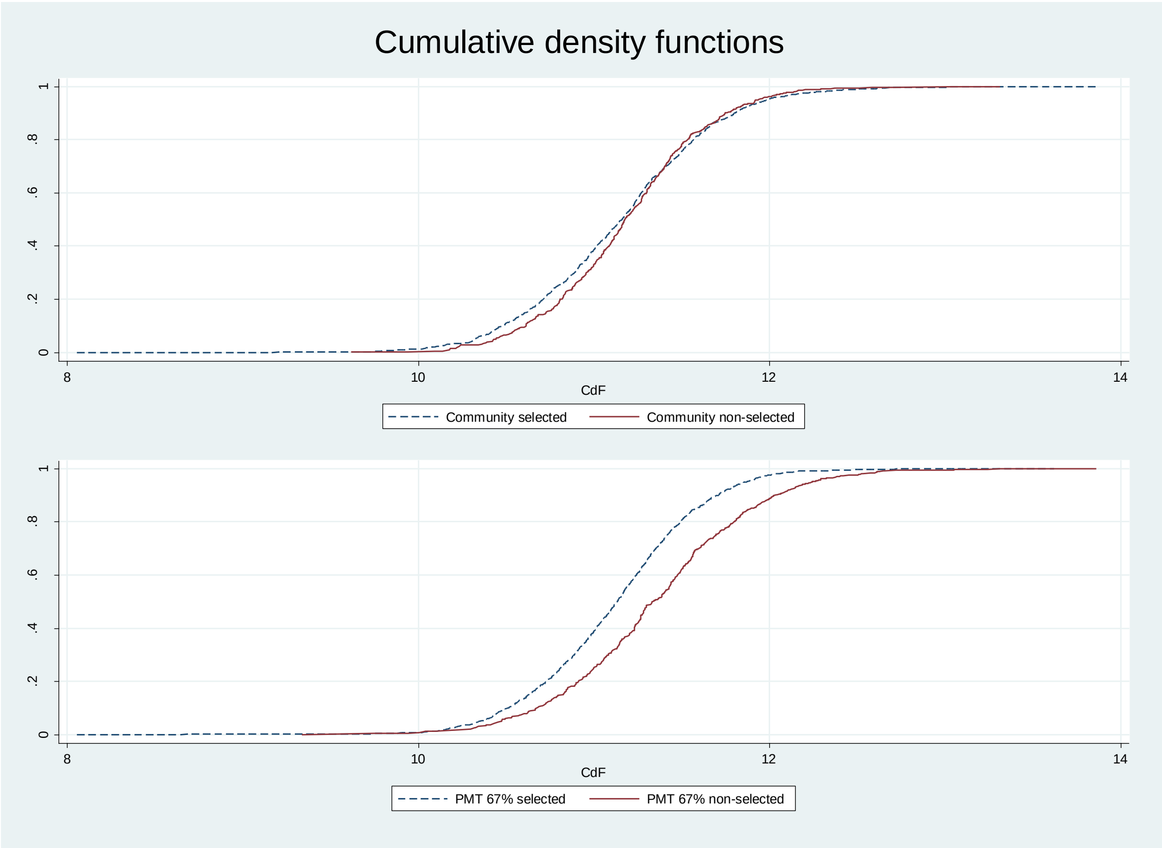
Note: Kernel densities of log of per capita consumption aggregate by targeting group. For comparison purposes, the PMT threshold is adjusted to obtain 67% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

Figure 4: Per capita consumption community and PMT



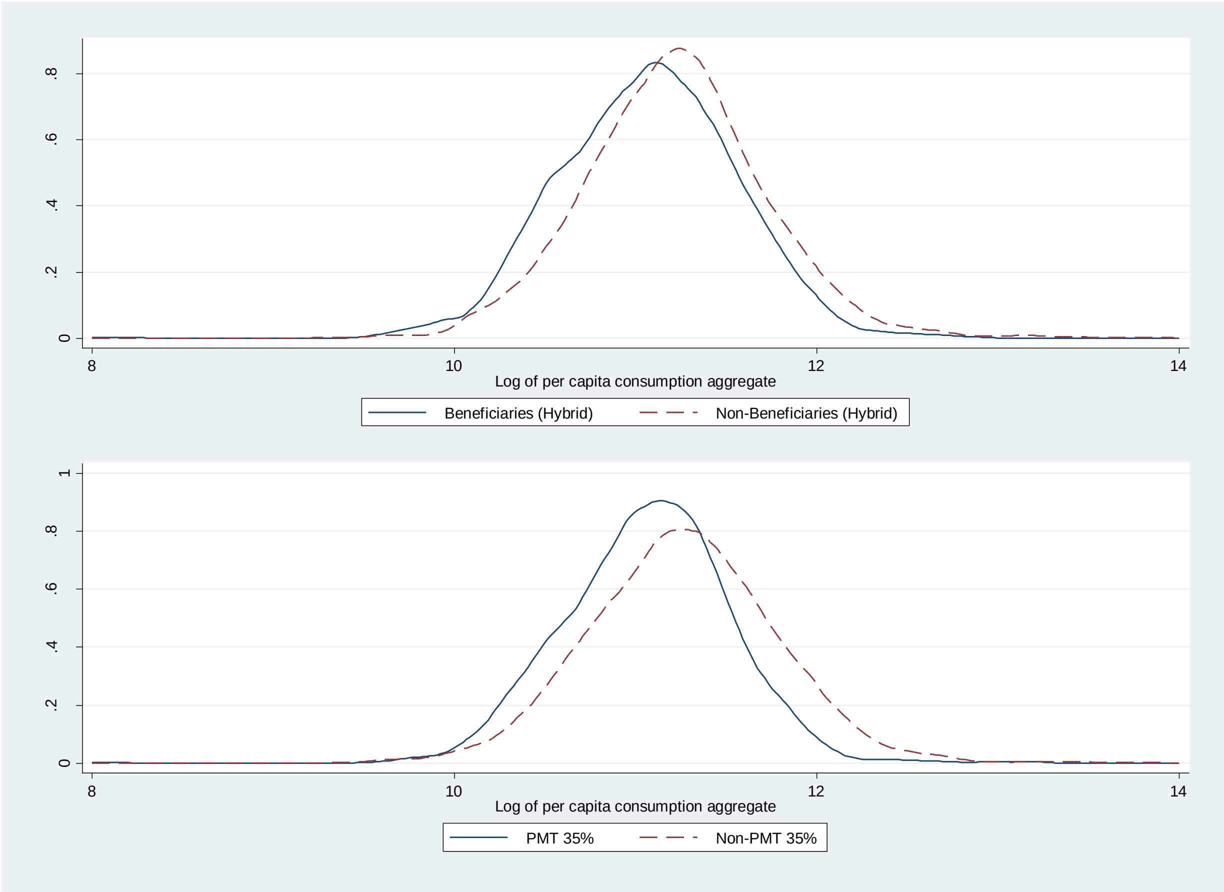
Note: Kernel densities of log of per capita consumption aggregate by targeting group and selection. For comparison purposes, the PMT threshold is adjusted to obtain 67% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

Figure 5: Per capita consumption by targeting group



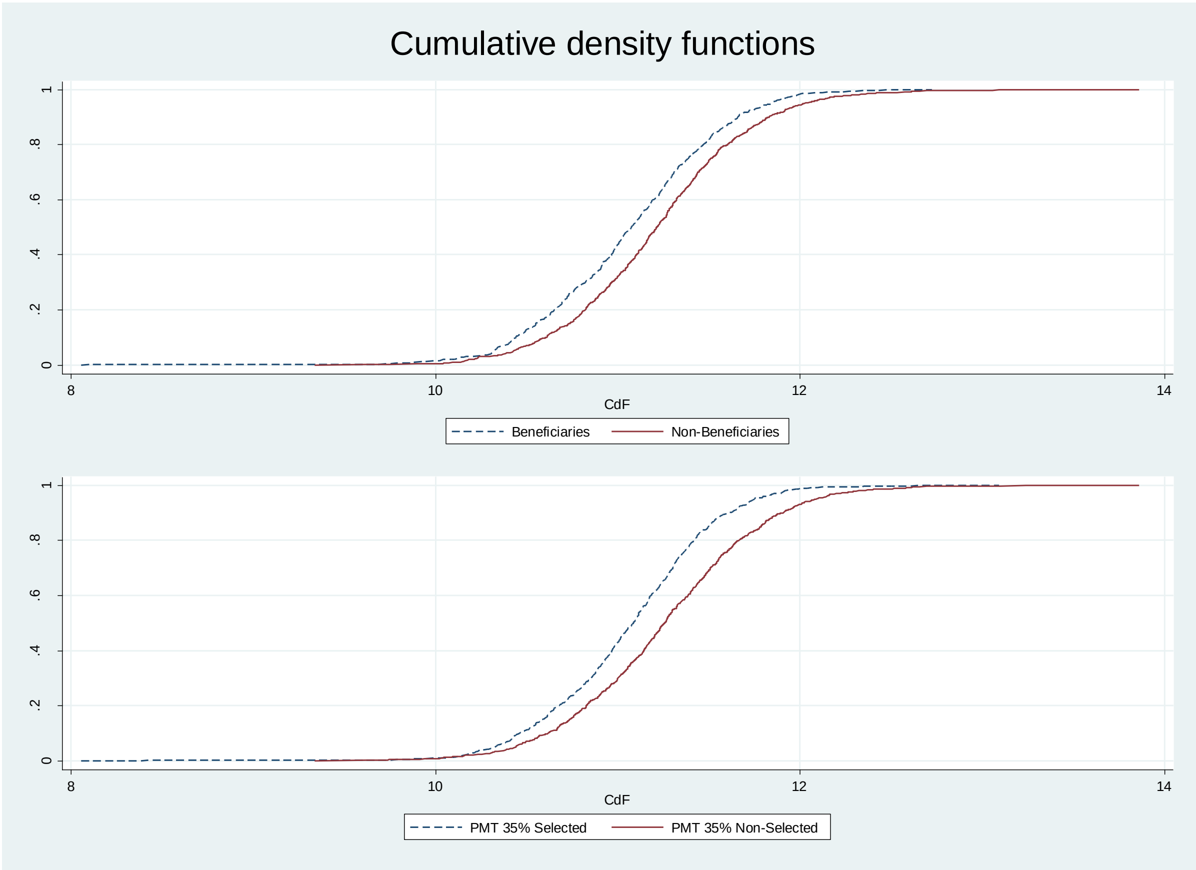
Note: Cumulative density functions of log of per capita consumption aggregate by targeting group and selection. For comparison purposes, the PMT threshold is adjusted to obtain 67% of the households targeted. Household size weights are used to obtain figures in terms of individuals. Sample weights are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

Figure 6: Per capita consumption Hybrid (project) and PMT



Note: Kernel densities of log of per capita consumption aggregate by targeting group. The 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). Household size weights are used to obtain figures in terms of individuals. Sample weights are used.

Figure 7: 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.

ESSAY3: Households' investments in durable and productive assets in Niger: quasi-experimental evidence from a cash transfer project

1. Introduction

Social safety nets, and cash transfer programs in particular, are increasingly popular tools for "reducing present and future poverty" of vulnerable households and "protection and promotion" (Grosh et al. 2008, Fiszbein and Schady 2009). While cash transfer programs have numerous and diverse objectives, all aim to reduce household poverty in the long-run, rather than merely rising consumption temporarily as a result of the transfers. This paper empirically explores one specific pathway to generate long-term sustainable improvements in household well-being: durable asset accumulation by poor households. Specifically, the study uses a controlled design to analyze differences between participants and non-participants investments in physical assets and productive activities after termination of an unconditional cash transfer (UCT) pilot program in Niger.

Pathways by which cash transfers can have a productive impact on beneficiaries and contribute to household income growth have been identified at the micro-economic level (Barrientos 2012). Transfers can alleviate the cash constraints directly or indirectly by facilitating access to credit and saving. Similarly, transfers can reduce the effect of risk and uncertainty ex-ante, promoting riskier and higher-return investments, and helping households to avoid harmful coping strategies in the face of adverse shocks (Macours, Premand, and Vakis 2012). Consistent with these theoretical expectations, the impact of Conditional Cash Transfers (CCT) programs have been shown to generate productive investments in Latin America (Gertler, Martinez, and Rubio-Codina 2012). However, impacts in very low income communities where marginal propensities to consume additional income are quite high have not been fully explored. This paper provides the first empirical evidence of long-term productive impact of cash transfers in Sub-Saharan Africa. The article also contributes to the poverty trap literature by identifying relaxation of barriers to asset accumulation as a specific pathway for long-term impact (Carter and Barrett 2006).

This study focuses on a pilot cash transfer program in rural Niger. The government of Niger has started to implement social safety nets, with a cash transfers component, as a means to fight food insecurity after recurrent food crises in the first decade of the millennium. One of the goals of this strategy is to “fight household’s vulnerability and help them to promote productive behaviors” (Maina 2010). The *Projet Pilote des Filets Sociaux par le Cash Transfert* (PPFS-CT) took place between October 2010 and March 2012, providing 2,281 households in the Tahoua and Tillabéri regions with monthly transfers of 10,000 FCFA (about 20 USD) for 18 months. This pilot has several unique features. First, it focuses on very poor, food insecure households in rural Sahel, one of the poorest regions of the world subject to recurrent crises of several types.[1] Second, the program delivers regular, foreseeable, monthly transfers rather than a one-time grant. Thirdly, the project offered very limited support activities during the pilot phase, effectively isolating the impact of the cash transfer from other interventions which are often bundled with this type of program as a “protection and promotion” package.[2] Fourth, and most importantly, the transfers ceased 18-months before the follow-up survey for measurement of the long-term improvements independently from current transfers, after households have been able to realize investments and benefit from them and also had the opportunity to disinvest and were possibly affected by adverse shocks.

[1] Niger has the lowest Human Development Index (HDI) in 2012 (see http://hdr.undp.org/en/statistics/).
[2] A notable exception is the promotion of *tontines* (local saving/credit systems), see section 4.

This paper evaluates the impact of the PPFS-CT on household investments 18 months after the last transfers, to assess the durable effect of the program after it has stopped, using quasi-experimental methods. The main impact identification strategy exploits the design of eligibility criteria for the project. Project eligibility is determined by the ranking resulting from the household Proxy Means Testing (PMT) scores that is computed from their characteristics. Households whose PMT scores are below a village-specific threshold are beneficiaries of the project. Because eligibility thresholds vary by village, households with similar PMT scores and yet different eligibility status can be compared in the analysis. Other quasi-experimental methods are used in combination with this primary strategy to assess the robustness of the results. First, a difference-in-difference approach is employed for variables included in the 2010 baseline survey and 2013 follow-up survey. Second, a regression discontinuity design is used for within-village comparisons of eligible and non-eligible households. Thirdly, propensity score matching, based on 2010 baseline characteristics, is used as well. Results across methods consistently show that cash transfers generate long-term sustained increases in household assets and productive activities after program termination.

The structure of the article is as follows. The next section briefly reviews the literature on cash transfers and possible impact pathways. The third section presents a simple asset accumulation framework. Section four describes the project, the data, and the empirical approach. Section five reports and discuss the results and robustness tests. The last section formulates policy recommendations and concludes.

2. Productive impact of cash transfers: review of evidence

The rise in direct cash transfers programs has been paralleled by rigorous impact evaluations, in Latin America where these programs originated, as well as in Sub-Saharan Africa where cash transfer programs quickly spread in the 2000s (Davis et al. 2012, Monchuk 2013). The impact of conditional and unconditional cash transfers have been widely studied using a wide range of experimental and quasi-experimental methods. Positive impacts on indicators of education, health, consumption, nutrition, as well as other dimensions, have been found (Fiszbein and Schady 2009, Garcia and Moore 2012, Baird et al. 2013). In addition, a recent but rapidly growing literature has analyzed and shown *productive* impacts of cash transfers (Barrientos 2012).

The first empirical studies come from cash transfer programs in Mexico. In the Procampo program in Mexico, a multiplier effect of between 1.5 and 2.6 has been estimated, suggesting that farmers are able to realize income opportunities which were previously constrained (Sadoulet, Janvry, and Davis 2001). This finding is confirmed by a seminal study of investments in productive assets from the beneficiaries of the Progresa/Oportunidades program (Gertler, Martinez, and Rubio-Codina 2012). Beneficiary households are found to invest up to 26% of the cash they receive in productive assets, increasing in particular animal ownership and production, bean cropping, land use, and micro-enterprise activities. Beneficiaries raise their agricultural income, which translates in long-term consumption increase of 1.6 peso for each peso received. Another study of the same program shows that an increase in asset holding is also found among non-beneficiaries in beneficiary villages, due to local economic spillovers (Barrientos and Sabatés-Wheeler 2010).

In Sub-Saharan Africa, where most of the population is rural and households are generally poorer than in Latin America, early cash transfers impact evaluations have often focused on understanding if (and how) cash transfer programs can help households develop revenue generating activities, through agricultural activities or non-agricultural micro-enterprises. Impact evaluation results are mixed in that some increases in investment are found, but increases usually do not occur across all the dimensions considered. In the CT-OVC program in Kenya, households showed improvements in some housing characteristics and increased savings and several private assets, but no increases are found in productive assets such as livestock holdings and land farmed (Ward et al. 2010).[3] Similarly in Zambia a UCT project in the Monze district, the Social Cash Transfer (SCT), is found to generate an increase in livestock holding, purchase of fertilizer and cash cropping, but not in private assets (Seidenfeld and Handa 2011). In three other districts, the SCT had a positive impact on micro-enterprises in urban areas and on livestock holding in rural areas, but not on cultivated land or private assets (Tembo and Freeland 2009).[4] In Malawi, the beneficiaries of the (unconditional) Social Cash Transfer Scheme accumulated private and productive assets (livestock and tools), and increased agricultural production through purchase of fertilizer and farm labor (Miller, Tsoka, and Reichert 2009). In Tanzania, the Community Based-CCT had a positive impact on non-bank savings, livestock, but not in private assets (Evans and Salazar 2011). The Ethiopian Productive Safety Net Program (PSNP) is a (largely cash-based) social protection program with an explicit objective of raising agricultural productivity. The PSNP had a mixed impact on yields, but a positive impact on asset accumulation, growth in livestock holding, use of fertilizer, durable investments in agriculture, and borrowing for productive purposes. The effect was clearer when transfers were larger and when participants also benefitted from complementary interventions (Gilligan et al. 2009, Hoddinott et al. 2012, Gilligan, Hoddinott, and Taffesse 2009). Another study of the PSNP compare food and cash transfers, and finds that in a context of growing inflation, food transfers

[3] Qualitative research indicates investment in farming activities and livestock for the most well-off beneficiaries, suggesting heterogeneity of impact.

[4] The impact was heterogenous, and significantly negative in some districts for micro-enterprises and cultivated areas. The positive impact on investments in school-related expenditures indicates potential trade-offs between physical and human capital investments.

were more popular and generated a higher growth in income and livestock, but a lower increase in non-productive assets (Sabates-Wheeler and Devereux 2010). Conversely, a comparison of cash vs. voucher delivery by an unconditional transfer program in DRC shows that cash transfers were more efficient: among others, recipients increasing their savings compared to voucher recipients, but not their private assets (Aker 2013). In summary, all these studies in Sub-Saharan Africa show an increase in savings, durable assets and/or productive activities, but the exact composition of households' investments depend on each program, and the long-term effect after program termination is not assessed.

In Niger, direct cash transfers have become very popular in recent years. A comparison of transfers delivered by mobile phone vs. by cash, in rural areas of the Tahoua region, shows that mobile phone transfers have several advantages in the short-term, including the depletion of fewer assets and an increase in the number of cash crops cultivated (Aker et al. 2011). Another study compares cash vs. food transfers in rural Zinder, and finds that food transfers result in increases in food security in the short-term, but households receiving cash spent more money to repair their dwelling and on agricultural inputs (Hoddinott, Sandstrom, and Upton 2013). Finally, a small-sample study of cash transfers in the Tillabéri region focused on food security showed that the project helped beneficiaries to rely less on debt to buy food, a harmful coping strategy (Tumusiime 2013). In addition to these quantitative analyses, an in-depth qualitative study of the "implementation gap" of cash transfer programs in Niger noticed that households invested in livestock and agricultural activities (Olivier de Sardan 2013).[5] These studies in Niger also point out the need for further research on the long-term effect of cash transfers.

[5] Some projects tried to prevent households to buy livestock in order to focus on other objectives (improving nutrition), which illustrates well the trade-off between immediate and long-term improvement in well-being for cash transfer implementers and recipients. According to the report, beneficiaries bought livestock nonetheless.

One-time, direct grants to stimulate micro-enterprises growth (and for other purposes) are a slightly different type of program than regular cash transfers used as social safety nets. However, articles which studied them are highly informative, since one-time grants are seen as a tool to promote productive investments by providing cash directly to households. A recent influential cash grant program experiment in Sri Lanka presents encouraging evidence of impact, with increased micro-enterprises returns of 60% per year, much higher than the local interest rate, suggesting threshold effects (consistently with the poverty trap literature) and puzzling credit market failures (De Mel, McKenzie, and Woodruff 2008).[6] Five years after the grant, survival rates and profits were still significantly higher for male enterprises (De Mel, McKenzie, and Woodruff 2012b). However, such long-term effects were not found in another experiment where grants were combined with training and given to female entrepreneurs. In this case, profitability increase is only temporary and not visible two-years after the baseline (De Mel, McKenzie, and Woodruff 2012a). Evidence from one-time grants programs in Sub-Saharan Africa contrasts with the promising findings elsewhere (for men). In semi-urban Uganda, cash grants do not generate any impact, whereas loans (and loans plus trainings) raised men's short-term profit by 54% (Fiala 2013). In urban Ghana, cash grants did not generate female micro-enterprises growth (in the short or long-term), and in-kind transfers only benefited larger businesses (Fafchamps et al. 2014).[7] However, a recent impact evaluation of a project giving large unconditional grants (lump-sum or monthly transfers) to rural households in Kenya found evidence of impact on several dimensions, including assets (58% increase, or 39% of the average amount transferred), investment in and revenue from livestock and micro-enterprises (large increases), but the impact on farm activities is ambiguous (Haushofer and Shapiro 2013).

[6] Similar results have been found by two of the authors in Mexico (McKenzie and Woodruff 2008).
[7] This literature usually finds a smaller impact (or no impact) on female micro-enterprises in Sub-Saharan Africa.

In summation, there is a reasonable amount of evidence that transferring cash directly to the poor generates *some* increases in productive investment. But the specific nature of the impact varies across programs. In the next section, we present a simple general model illustrating why in the rural Africa contaxt household investments may be very low (or inexistent) and how cash transfers can change this situation.

3. A simple model of household investment

A simple model of household saving behavior, following Deaton (1990), illustrates the process of asset accumulation and how cash transfers can enable households to increase (or trigger) asset accumulation. Let households maximize intertemporal utility:

(1) $$u = E_t\left[\sum_t^{\infty}(1+\delta)^{-t}v(c_t)\right]$$

where $\delta > 0$ is the time preference parameter, c_t household consumption at time t, and $v(c_t)$ instantaneous utility associated with c_t (which is assumed to be a concave, monotically increasing function). The budget constraint associated with consumption, physical assets A, real income y_t and real interest rate r, shows the process of asset accumulation for the next period:

(2) $$A_{t+1} = (1+r)(A_t + y_t - c_t)$$

The associated Euler equation is:

(3) $$\lambda(c_t) = E_t\left[\frac{(1+r)\lambda(c_{t+1})}{(1+\delta)}\right]$$

where $\lambda(c_t) = v'(c_t)$, the marginal utility of consumption at t, a monotically decreasing function, from the assumption of concavity of $v(c_t)$ – which is related to decreasing absolute risk aversion. This guaranties a precautionary motive for saving.[8] Cash transfers can be seen, in this framework, as a component of y_t, because they temporarily increase income. Thus, a first obvious cause for cash transfers to increase savings is when cash transfers are temporary, because households want to spread out the increase of consumption over time (permanent income hypothesis).[9]

Now, let's assume that: i) households value present time highly so that $\delta > r$; and ii) households cannot borrow so that $A_t \geq 0$.[10] When households do not want to borrow (first case), the Euler equation (3) still holds. When households do want to borrow but cannot (second case), the following conditions now holds:

(4) $$\lambda(A_t + y_t) > E_t\left[\frac{(1+r)\lambda(c_{t+1})}{(1+\delta)}\right]$$

$$c_t = A_t + y_t\,, \qquad y_t \leq c_t\,, \qquad A_{t+1} = 0$$

This means that households do not accumulate new assets and consume all current assets. Both cases can be summarized as such:

(5) $$\lambda(c_t) = \max\left\{\lambda(A_t + y_t), E_t\left[\frac{(1+r)\lambda(c_{t+1})}{(1+\delta)}\right]\right\}$$

Equation (5) suggests that consumption is a function of total wealth at hand, $x_t \equiv A_t + y_t$, such that:

(6) $$c_t = f(x_t)$$

As shown by Deaton (1990), by inverting the monotically decreasing function $\lambda(.)$, (5) becomes:

---

[8] Savings are commonly made in productive assets such as livestock in rural Sub-Saharan Africa. Although there is not a perfect equivalence between savings and productive investment, this simple theoretical framework does not need to differentiate them to illustrate how cash transfers can lead to productive investment.

[9] Note that this increase in savings for consumption smoothing purposes is expected in the short term, but these savings are consumed over time, so that the effect found two years after the transfers have stopped may be small, especially if δ is large.

[10] A large δ means that households have urgent consumption needs so that they value consumption more than market real interest rate r. For economic justifications of the two assumptions i) and ii), see Deaton (1990) or Adams (1998).

(7) $$c_t = f(x_t) = \min\left\{x_t, \lambda^{-1}\left(E_t \frac{(1+r)\lambda(c_{t+1})}{(1+\delta)}\right)\right\}$$

This means that when total wealth x_t is low, all wealth is consumed at t, such that for low levels of wealth, a unit increase in x_t translates into a unit increase of c_t: all cash transfers would be used immediately for consumption purposes. However if wealth increases enough, there is a discontinuity in the consumption increase, and instead of consuming x_t, the household saves part of the wealth and only consumes $\lambda^{-1}\left(E_t \frac{(1+r)\lambda(c_{t+1})}{(1+\delta)}\right)$.

Thus, according to this model, a *sustainable* increase in assets can occur under two conditions: i) while households receive cash transfers, the increase in wealth due to the transfers at time t is important enough to shift the consumption function from x_t to $\lambda^{-1}\left(E_t \frac{(1+r)\lambda(c_{t+1})}{(1+\delta)}\right)$; ii) after program termination, the savings accumulated during the cash transfers period are important enough so that when the transfers stop, A_t is large enough and households do not revert to a pre-transfers saving behavior by consuming x_t (and thus depleting assets they accumulated).

Other models lead to a similar, positive effect on investment and asset accumulation. For example, Ramsey models lead to solutions in form of a Bellman equation that can explain asset investments related to cash transfers (Fafchamps et al. 2014) as well as ex-ante and ex-post behaviors with respect to risk (Elbers, Gunning, and Kinsey 2007). Lack of asset investment can also be explained by the presence of a poverty trap with two technologies. Some households would be stuck in a low equilibrium (a low-risk, low-return technology) and need additional capital (because of the sunk cost or riskiness of the high-return technology) to cross the threshold where adoption of the high-return technology becomes more profitable (Barrett, Carter, and Ikegami 2008, Carter and Barrett 2006). Finally, a micro-enterprise model can be employed to show that lack of access to credit or insurance causes underinvestment in the productive activity and that cash transfers can alleviate these constraints (De Mel, McKenzie, and Woodruff 2008). All these models suggest a positive impact of cash transfers on household productive investments but a minimum threshold level of transfers may be needed to spark asset accumulation. The next section presents the empirical approach and the data used in this paper to assess if in the Niger PPFS-CT, beneficiary households have invested in productive activities, as suggested by this simple model.

4. Data and empirical approach

Project description and data collection

The PPFS-CT was designed to address chronic food insecurity in Niger and household's high vulnerability in general, in a context of recurring droughts and other economic adverse shocks. This pilot project was led by the government of Niger with technical assistance from the World Bank.[11] The pilot took place in 52 villages of the Tahoua and Tillabéri regions and reached 2,281 beneficiary households. They received monthly transfers of 10,000 FCFA (about 20 USD) for 18 month, delivered in cash in the villages, between October 2010 and March 2012. One feature of the project is that it encouraged beneficiaries to set-up of *tontines* and involved micro-finance institutions (MFI), which were put into contact with local farmers organizations.[12]

Household targeting was based on a Proxy Means Testing (PMT), which is an increasingly common targeting method in Sub-Saharan Africa (Stoeffler and Mills 2014, Del Ninno and Mills 2014). The PMT formula was calculated beforehand, based on a regression on consumption data from a nationally representative survey (Katayama 2010). By using this formula, a PMT score

[11] The pilot project was scaled-up to the region. The regional program started in March 2013 and will eventually reach 140,000 poor households in different geographic areas. Qualitative fieldwork has been conducted in the areas covered by the scaled-up program.

[12] *Tontines* are local saving/credit systems where each member brings cash to a common pot each time they meet (daily, weekly or monthly). Members rotate so that at each meeting, one of them takes all the cash from the pot and spends it. *Tontines* are often referred to as Rotating savings and credit association (ROSCA) in English. According to project managers, almost 90% of the beneficiaries took part to *tontines* (personal communication).

was computed for each household in project villages, based on the characteristics of the households (demographics, education, livestock, etc.). The PMT score approximates a long term expenditure /consumption level, so that a low PMT score is a proxy for a low consumption level. In each village, a village-specific PMT eligibility threshold was chosen so that 30% of the households were beneficiaries. Thus, a household with a score below its village threshold received transfers from the project. Ex-post assessments of the targeting method show that the PPFS-CT reached poor households relatively efficiently (McBride 2014).

This study uses two rounds of data collection, in Fall 2010 and Fall 2013, i.e. before and after project operations (from October 2010 to March 2012). In September 2010, the PMT (baseline) questionnaire was administered among all households of the project villages. The information collected in this baseline survey is limited: it includes mostly variables necessary to construct the PMT formula, as well as some information on shocks and food security (only in Tahoua). Additional data were collected during a follow-up survey in the Fall 2013 among 2,000 households, when about 20 beneficiaries and 20 non-beneficiaries were randomly surveyed in each of the 52 project villages. This follow-up survey includes all the modules of the 2010 questionnaire, and additional modules on investments (private assets, local credit, micro-enterprises, agriculture), education, health and consumption.[13] The methodology employed to evaluate the impact of the cash transfer program on households' investments is driven by data availability. In particular, the fact that some variables are included in the 2010 baseline survey, but most of investment variables have only been collected in the 2013 follow-up survey.

[13] In October 2011, another round of survey was conducted, including a consumption and a food security modules (but not all the PMT variables). It was not possible to use this survey because of data quality issues. An analysis of these data suggests a possible reduction of food security caused by the project, but results are ambiguous (McBride 2014).

Table 1 presents descriptive statistics for the whole 2013 sample (not only households in the PMT range used for the SD analysis). After data entry, cleaning and merging with the 2010 dataset, 1,579 questionnaires are usable for the analysis (see attrition tests in section 5). As expected from the PMT formula used, non-beneficiary households are smaller, have more physical assets, and have higher PMT scores on average. However in 2013, beneficiary households have a higher level of livestock, MEs activities and *tontine* usage.

Empirical approach and identification strategy

To study the effect of cash transfers on household i's investments, we try to estimate the impact of being beneficiary on several variables of interest y_i. The first set of outcomes considered is related to the use of *tontines* (number of *tontines*, amount received, usage), which were project direct output and are an important vector of investments in rural Niger. Then, several investment dimensions are considered: housing quality and living standards (house material, access to water, toilets, etc.); physical assets investment (number and value of physical assets); livestock (stock at the survey in 2013, stock 12 months before, difference between 2012 and 2013, consumption and sales); micro-enterprises (MEs) (number of MEs, revenues, charges and profits, value of equipment); and agricultural investments (surface cultivated, quantity produced and yields, input spending, type of crops). Finally, variables related to economic shocks (type of shocks, coping strategy) are studied to understand if potential investments translated into better households resilience to adverse shocks. These variables cover a wide range of possible household investments and other outcomes related to investments.

The main identification strategy, for impact variables only observed in the follow-up survey (i.e. most variables), exploits the design of the project: in particular, the difference in eligibility thresholds across villages, since the PMT cut-off was adjusted by the project to include 30% of the population of each village as beneficiaries. Because the eligibility threshold varies by villages, it is possible to have households with similar PMT scores but different eligibility status (see figure 1). The method employed is to use a subset of the whole sample: households with PMT scores in a certain range will be either beneficiaries or non-beneficiaries depending on the village to which they belong. This difference in eligibility status is not due to random assignment, which is why the identification strategy is quasi-experimental rather than experimental. However, for beneficiary (treatment) households, non-beneficiary (control) households with similar PMT scores constitute a credible counter-factual of what would have happened to beneficiary households in the absence of the program.[14] PMT scores range boundaries are selected so that each household with a given PMT score can be either beneficiary or non-beneficiary: from the lowest PMT threshold ($PMT\_threshold_{min}$, in the village with the lowest overall PMT threshold) to the highest PMT threshold ($PMT\_threshold_{max}$, in the villages with the highest overall PMT threshold). With this sub-sample, the estimation is a Simple Difference (SD) OLS regression:

$$(8) \qquad y_i = \beta_0 + \beta_1 \mathrm{B}_i + \varepsilon_i \,, \qquad i \epsilon A$$

where B_i is a dummy variable indicating that the household is beneficiary (received cash transfers), and $i \epsilon A$ if $PMT\_threshold_{min} \leq PMT\_score_i \leq PMT\_threshold_{max}$, and β_1 measures the impact of the cash transfer. We also show results based on equation (8) with errors ε_i are clustered at the village level to take into account village shocks and effects; and in a third variant, with village dummies– with the same purpose.

[14] The main two assumptions for a selection bias to be avoided are: i) the PMT difference between beneficiaries and non-beneficiaries, in the subsample, is small enough for them to be “similar”; ii) the fact that some villages will have more beneficiaries and other more non-beneficiaries does not introduce another selection bias. Village dummies are added in some specifications to be certain to control for the latter possible bias.

Robustness tests

A small number of variables (some physical assets, livestock stock) are also included in the baseline (2010) survey. For these variables, it is possible to use a difference-in-difference (DID) OLS regression as a first robustness test:

$$y_{i\epsilon A,t} = \beta_0 + \beta_1 \mathrm{B}_i + \beta_2 T_t + \beta_3 \mathrm{B}_i * T_t + \varepsilon_{i,t} \quad (9)$$

where T is a dummy variable for $t = 2$ and β_3 measures the impact of the transfer. As for SD OLS regressions, we also present results from (9) with errors ε_i are clustered at the village level to take into account village shocks and effects.

Second, because village conditions may influence household outcomes, village-level discontinuity around the eligibility threshold is employed as another identification strategy as another robustness test. This identification strategy consists in comparing households with similar PMT scores within the same village around the eligibility threshold. After normalizing the PMT threshold[15], we use a regression discontinuity (RD) design to estimate the impact of the cash transfer:

$$\tau_{RD} = E[Y_i(1) - Y_i(0)|X = c] = \lim_{\varepsilon \downarrow 0}[Y_i|X_i = c + \varepsilon] - \lim_{\varepsilon \uparrow 0}[Y_i|X_i = c + \varepsilon] \quad (10)$$

where τ_{RD} is the Local Treatment Average Effect (LATE) obtained via RD, $Y(1)$ is the outcome of interests for treated observations and $Y(0)$ for untreated observations, c is the normalized PMT threshold and X_i is the PMT score of household i in 2010 (the forcing variable of the RD). The linear empirical specification used in the analysis takes the following form:

$$y_{ij} = \beta_0 + \beta_1 \mathrm{B}_i + \delta(X_i) + \mu_j + \varepsilon_i \quad (11)$$

where μ_j are fixed-effects for village j of household's i.

[15] Because the PMT threshold varies by village, household's PMT score is normalized by subtracting the village PMT threshold to all PMT scores in this village (in such way that the common normalized PMT threshold is 0).

The last robustness test consist in employing a Propensity Score Matching (PSM) estimator to compare beneficiaries to non-beneficiaries with similar characteristics (Caliendo and Kopeinig 2008, Rosenbaum and Rubin 1983). The propensity to participate to the program $P(X)$ is estimated via a probit regression including 2010 baseline characteristics as covariates X. Then, the Average Treatment Effect (ATT) can be estimated via PSM:

$$\tau_{ATT}^{PSM} = E_{P(X)|D=1}\{E[Y(1)|D=1, P(X)] - E[Y(0)|D=0, P(X)]\} \quad (12)$$

where $D = 1$ indicates treatment, $Y(1)$ is the outcome of interests for treated observations and $Y(0)$ for untreated observations. The PSM estimator is estimated with Stata (Leuven and Sianesi 2014).

5. Results & discussion

Tests of attrition and balance

The level of attrition in our sample is relatively high: 361 questionnaires are lost or not usable out of 2,000 sampled, or 148 out of the 932 in the PMT range used for the main identification strategy. Attrition is due to the loss of questionnaires in three villages (108 questionnaires), the impossibility to match identifiers, but also failure to survey households on the field (186 questionnaires out of 2,000 sampled). A formal test of difference at baseline (2010) between attrition and non-attrition households is performed in the PMT range used for the main analysis (Table 2). Among all the variables collected in 2010, only ownership of cart (lower) and PMT score (higher) are significantly different at 5% for attrition households. This test suggests that attrition does not affect results of the main identification strategy.

In Table 3, the difference between beneficiaries and non-beneficiaries at baseline (in 2010) is formally tested in the sub-sampled used for the SD analysis (within the range of PMT score thresholds). All the variables tested are included in the PMT formula, so significant differences across groups are expected. Besides the difference in PMT scores (beneficiaries have lower scores), the main significant differences are household size and the number of goats. The difference in motorcycle and motor-pump ownership is also significant, but almost no household owns these items at all. These tests indicate that our SD design did not produce a perfectly balanced sample, but limited the differences between the treatment and control groups in terms of number and the magnitude of these differences. Moreover, control households appear to be better off, which makes positive effects of the treatment harder to find, but does not threaten their validity (see section 4).

Results

The Simple Difference (SD) results (the main identification strategy, equation (8)) are presented in Table 4, 5 and 6, in three different specifications: without (model 1) and with (model 2) standard errors adjusted at the village level, and with village dummies (model 3). Rows indicate for each outcome of interest the coefficient associated with being “beneficiary” of the PPFS-CT, which is positive and significant for several of the outcomes considered.

First, the long-term impact of the project on *tontines* (local group saving/credit systems) is measured, as they are almost a direct output of the project (see section 4). Also, *tontines* are an important vector of investment in rural West-Africa. There is a large and significant increase of the use, number, and amount invested in and received from *tontines* among beneficiary households (Table 4). This translated into an increase in consumption from *tontine*-funds, but also investment in productive activities and private assets, as well as other usages. These results suggest that beneficiary household were able to continue to participate in the *tontines* set-up during the project after its termination.

Secondly, we analyze how this greater participation in tontines translated into investments from beneficiary households (Table 5). A large impact on housing and standard livings (Panel A) is not expected because they did not appear as priority investments for most households and because the number of households with solid walls or roofs at baseline was very low. However, there are some indications of improvement in access to clean water, toilets, and solid walls according to some specifications, but not in solid roofs, home lighting or cooking fuel. There are indications of investment in private assets (Panel B) from beneficiary households, who have a higher number of different assets than non-beneficiaries in 2013. The value of assets purchased in the last 3 years is also greater for beneficiaries (by about 20,000 FCFA). But overall, results are not robust across all specifications for private assets.

On the other hand, the impact on livestock is large and clearly significant (Panel C). Beneficiary households have on average 0.3 TLU more than non-beneficiaries, which represents almost half a cow (or 3 goats, or 30 chicken). In FCFA, this increase represents about 60,000 FCFA (one third of the total transfers received). This has not translated into a significant increase of livestock sales (according to most specifications), but into a significant increase in consumption from own livestock. Finally, the difference between livestock in December 2013 and December 2012 (asked retrospectively in the 2013 survey) is insignificant and very small, suggesting that beneficiary households are not depleting livestock assets since the end of the project.

A clear effect on micro-enterprises (MEs) activities is not found (Panel D). The point estimates indicate a large increase in revenues, charges and profits from MEs, but the standard deviation is too large for these coefficients to be significant. This was perhaps to be expected given the relatively small number of MEs, and their diversity in terms of activities and scale. There is indication of an increase in the number of transportation MEs, as well as in equipment purchased in the last 3 years, but the magnitudes are small.

On the other hand, there is evidence of improvement in agricultural activities (Panel E) for beneficiaries. As expected, the project did not seem to have overcome initial differences in land structure (owned and borrowed surfaces, etc.). Also, a smaller number of beneficiaries seem to use any fertilizer. However, for the entire sample, fertilizer spending is higher for beneficiaries, which means that among beneficiaries those using fertilizer compensate for households not using fertilizer. There is also a small but significant increase in quantity produced and yields from beneficiaries. Note that when village dummies are used, there only remains the positive effect on fertilizer spending, number of crops farmed, quantity produced and yields.

Thirdly, we study if these investments translated into a better resilience of households to shocks (Table 6). Occurrence of shocks during the last 12 months (Panel D) for beneficiary households has not clearly changed in 2013, except the loss of private transfers[16], and interestingly, a lower rate of occurrence of theft for beneficiary households – perhaps because they have been identified as "poor" by the project – indicating that if cash transfers generated negative feelings in the community, they did not translate into stealing from beneficiaries despite the increased opportunity generated by the circulation of cash and the purchase of livestock.[17] Regarding household resilience to shocks, the evidence is not clear: beneficiaries do not differ from non-beneficiaries in terms of harmful coping strategies (depletion of assets, etc.) but they mention using less coping strategies overall, which does not mean that they have better coped with shocks.

[16] This loss of private transfers is puzzling because it occurred at least 6 months after project termination. These results may be due to a confusion in the recall period from respondents and/or to a confusion between project cash transfers and private transfers.

[17] There is actually no evidence of jealousy or feeling of injustice towards beneficiaries, according to the quantitative survey and the qualitative work conducted in the project.

Robustness tests results

As detailed in section 4, several other quasi-experimental methods are used to assess the robustness of the results. First, a Difference-in-Difference (DID) estimator measures the impact of the program on beneficiaries in 2013 for a limited number of outcomes included in the 2010 baseline survey (Table 7). DID results do not differ largely from Simple Difference estimates which increases confidence in the SD results. A significant impact on access to toilet is found, but no other housing and living standards variables see a significant coefficient.[18] The number of assets considered being limited to those included in the baseline survey (not all of these included in the 2013 list), no significant impact is found on the number of different assets. However, the impact on livestock is still clearly significant and slightly larger than the SD estimates, because beneficiaries had less livestock than non-beneficiaries at baseline.

RD results are presented in Table 8. There are several econometric issues that decrease the reliability of RD estimates, which is why RD is not considered as the main identification strategy of this study. First, some variables of interest enter positively into the construction of the forcing variable itself (PMT score) at baseline: households with higher livestock at baseline have higher PMT scores, which introduce a downward bias and make it more difficult to expect a significant impact. Second, the PMT threshold used is arbitrary, because village thresholds vary, requiring an adjustment to obtain a common threshold (see section 4). This adjustment makes households with similar *adjusted* PMT scores very different in terms of real PMT scores (i.e. having different characteristics, expected wealth, etc.). This is likely to greatly increase the variance of the outcome around the threshold and limit the relevance and significance of the discontinuity.

[18] Note that by comparing 2010 and 2013 values for housing characteristics such as roof and walls quality (for which definitions are not consensual), it seems that the questions have not been asked the same way in the two surveys. While questionnaires are identical, surveying firms have changed. For these variables, SD estimates may be more reliable.

Third, it appears that at certain level of bandwidth, continuity of the forcing variable (an important assumption to obtain valid RD estimates) is violated since a significant jump in the forcing variable is observed (Lee and Lemieux 2009). Despite these limitations, RD is useful to observe behavior of outcomes of interest around the discontinuity at the village-level.

A significant impact is found for several of these outcomes, but not as many as in the SD or DID results. This may be, in part, due to the fact that there are few observations (and even fewer in each village) close to the PMT threshold with the bandwidth used (Table 8). The main difference with SD results is that RD results suggest that beneficiary households still encounter a greater occurrence of shocks, and use more coping mechanisms.[19] Overall, RD estimates confirm that beneficiary households retained *tontines* after project termination, did not invest a lot in their dwelling or in MEs, but acquired some private assets, and realized significant investments in livestock and agricultural activities.

The last robustness test is to compute ATT estimates for the outcomes considered (see section 4). The propensity score (propensity to be treated, i.e. beneficiary of the project) is computed from the PMT score, since it is known that project eligibility is determined by this PMT score. One-on-one matching without replacement is computed for all households, not only those in the PMT range of the main specification.[20] The test of balance between treated and control observations is performed for unmatched (before PSM is employed) and matched observations (after PSM weighting). The test show that standardized percentage bias is relatively small, except for

[19] RD estimates of the effect on shocks, however, are limited because shocks are relatively rare events. Thus, estimation is not possible (with village effects) for many of the shock variables.

[20] Several other PSM specifications have been tested, including: a specification for households in the PMT range only; a specification using all baseline (2010) variables instead of the PMT score only; and a specification using a different matching algorithm, i.e. radius matching. Results are relatively similar across specifications, but results from the PMT range specification are much closer to results from the main identification strategy. Also, the magnitude of the effect tends to be larger in PSM specifications.

household size and the PMT score itself (which was expected) (Figure 2). Common support is not found only for 89 households, which means that most observations are used.

Results from PSM are very close to those obtained from the main identification strategy, with two main exceptions (Table 9). First, the PSM estimator finds a significant, negative effect on house quality, which confirms that most households have not invested in their dwelling and not caught up with non-beneficiaries (house quality variables are included in the PMT score). Second, the effect on agricultural activities is more pronounced with the PSM estimator that with the main specification: all coefficients are positive, and a significant effect is found on land owned, fertilizer spending, number of crops and quantity produced. Overall, these three tests confirm the robustness of the results obtained with the main specification.

Discussion

Taken as a whole, these results suggest that households have not realized large private investments (in private assets, housing and living standard improvements) but have rather focused on productive activities to raise future revenues. The effect is particularly large and clear for livestock and agriculture, which are the primary sources of income in rural Niger. Beyond statistical significance, the magnitude of project beneficiaries investments is also noteworthy. For livestock alone, they represent 74,992 FCFA (according to the DID estimator), whereas beneficiary households only received 10,000 FCFA per month, and 180,000 FCFA over the whole duration of the project (18 months). The amount invested raises to 94,284 FCFA by adding investments in household belongings, which is more than half of the total cash received. Because monthly transfers are relatively small compared to the size of investments required in livestock and agriculture *tontines* may have been key to carry out these investments: the average value of a sheep is 37,500 FCFA, whereas monthly transfers were 10,000 FCFA only. While the transfers did not clearly lead to a better resilience to shocks in the long-run, 18-months after they stopped, shocks do not seem to dissipate acquired assets, as indicated by the similar level of livestock in 2012 and 2013 for beneficiary households.

Considering the theoretical framework outlined in section 3, it appears that the PPFS-CT was able to shift consumption-saving decision behaviors of beneficiaries away from a full-consumption pattern towards a partial-saving one, meaning that they accumulated assets during the project. Interestingly, these investments have not been geared towards private assets or improvement in housing and living standards, from which households could have derived an immediate consumption flow (e.g. lighting at night, use of a motorcycle, etc.). Instead, households have focused on *productive* investments to raise their long-term revenues, showing a concern for longer-term inter-temporal consumption improvements. This priority was noticed during qualitative fieldwork, where most households emphasized the need to “keep something when the project will end in two years”. However, choosing to invest in productive activities (including agricultural inputs) means going beyond the idea of “keeping something”: households’ investment choices illustrate their objective of raising long-term income and agricultural productivity and to retain accumulated assets.

This interpretation of the results is in contradiction with the critics of social assistance, which argue that cash transfers would create dependency for its beneficiaries, who would passively raise consumption only during the time of and by the amount of the transfers. While evidence from elsewhere is already at odds with this widespread fear (see section 2), the study of the Niger PPFS-CT suggests that even very poor households – living in Sahelian rural areas lacking infrastructures and prone to adverse shocks – are able to actively take advantage of cash transfers.

The large increase in the use of *tontines* (strongly encouraged by the project) and their survival after project termination have important implications for the household finance-related development projects and policies such as savings incentives and access to credit. Our results suggest that the main constraint faced by very poor rural households in Niger for investing is not the lack of financial instruments or other social or technical constraints, but the lack of funds to invest. By receiving predictable amounts of cash over 18 months, these households were able to satisfy immediate consumption needs and thus find the financial space required to save and invest. Also, the provision of regular cash transfers allowed them to take part to these credit/saving schemes, by making them credible participants able to bring their contribution each time. The fact that *tontines* survived project termination shows that households saw the potential of these financial instruments and remained credible *tontines*-participants. These results suggest a strong potential for complementary activities associated with cash transfers such as those related to financial instruments (saving or credit) and to agricultural extension (e.g. training or technology adoption projects) since agricultural households seem to have reacted quickly to the alleviation of the cash constraints.

Finally, several limitations to the impact evaluation presented in this paper are worth noting. First, the precise mechanisms leading to and limiting investment are not fully investigated, due to limitations of the survey (e.g. no measure of risk aversion, etc.) or to the evaluation design. Among others, there is only one arm of treatment rather than comparing different type of interventions or different levels of treatment (e.g. changing the level or temporality of the cash transfers). Second, there may be some concerns with internal validity due to the composition of the counterfactual in the main identification strategy: control households belong to poorer villages, since they are not among the poorest 30% while having similar PMT scores than beneficiary households.[21] Conversely, control households have higher PMT scores than treatment households, in each village and overall – which is clearly a downward bias.[22] Also, local spillover effects generated by the cash transfers in the village may cause contamination of the control group.[23] Finally, the external validity of the study is limited, because the sample is not representative of the country or of the region, and general equilibrium effects due to the transfers (e.g. inflation) are not taken into account. For these reasons, this paper does not claim to assess the impact of any cash transfer or social safety nets intervention in the world, but rather to add empirical evidence of cash programs potential in a rural, extremely poor, African environment.

6. Conclusion

This article studies the impact of a cash transfers on households' investment in assets and productive activities 18 months after termination of a cash transfer project in rural Niger. By comparing beneficiary households to non-beneficiaries with similar PMT scores, a positive impact on livestock, agricultural activities and other assets is found. Notably, beneficiary households increase their livestock by half a cow on average (or equivalently, three goats or thirty chicken), corresponding to more than half of their baseline stock (in TLU). The findings suggest that social safety nets can be efficient tools to help households build a lasting asset base in the medium-term, and thus tackle some of the "deep roots" of poverty.

[21] This issue could create a positive bias on the impact estimate if beneficiary households benefit from the better overall economic position of their village (for instance by receiving higher agricultural wages). Conversely, the bias could be negative if they suffer from their lower position in a richer village (for instance if their relative poverty prevents them to have access to leading positions in the village). Adding village-effects partly resolves this potential bias, but given the few number of observations per village, there is a large loss of degrees of freedom (especially for outcomes with few non-zero values such as "having a solid roof").

[22] This downward bias does not cast doubt on the significance of a positive impact, but generates a higher probability to find insignificant results.

[23] There are evidence of such a spillover effect in other cash transfers programs (Angelucci and De Giorgi 2009). Again, this contamination would only create a negative bias on the impact estimate; consequently it does not cast doubt on the significance of a positive impact.

These results confirm promising findings from Latin America (and increasingly, from Sub-Saharan Africa as well) regarding sustainable asset accumulation by beneficiaries of cash transfer projects. Recipients appear to react to cash transfers by investing rather than only consuming the transfers. This article is one of the first to study, in Africa, changes in productive investments stemming from monthly transfers 18 months after they have stopped. The findings demonstrates the potential for cash transfers to stimulate investment even in poor rural households which, because of multiple constraints, are not expected to take advantage of the cash transfers to realize medium-term investments and accumulate assets.

These findings suggest a strong potential role for complementary activities accompanying cash transfer programs to help households realize profitable *investments*. Indeed, in Niger, *tontines* appear to be key successful means for assets accumulation, suggesting a great potential for complementary saving and micro-credit programs. Because household investments strategies are diverse and include agricultural capital and inputs, agricultural training programs for instance could be proven useful to foster household productive investments.

The results, while promising, also raise many questions regarding the precise mechanisms which foster asset accumulation. The duration of the cash transfers for instance need to be more careful studied to understand what type of productive impact can be expected from households and for how long. The temporality of delivery and magnitude of transfers are likely to affect whether or not households can reach the threshold where immediate consumption needs are satisfied and asset accumulation becomes possible. More studies are needed to determine this threshold in a context of cash transfer program. The role of risk alleviation, thought as one of the main channel through which social safety nets improve households' well-being and stimulate investments, also needs to be identified. Finally, while investments have positive aggregate effects at the local economy level, at the household level they are a means to improve households' well-being rather than an end. For this reason, the long-term improvements in education, health, consumption, food security, living standards, and other dimensions need to be studied to understand the complementarities and trade-offs between the productive impact of social safety nets on household assets and investments, and impact on households human development and overall well-being.

References

Adams Jr, Richard H. 1998. "Remittances, investment, and rural asset accumulation in Pakistan." *Economic Development and Cultural Change* no. 47 (1):155-173.

Aker, J., R. Boumnijel, A. McClelland, and N. Tierney. 2011. "Zap It to Me: The Short-Term Impacts of a Mobile Cash Transfer Program."

Aker, Jenny. 2013. "Cash or Coupons? Testing the Impacts of Cash versus Vouchers in the Democratic Republic of Congo." *Center for Global Development Working Paper* (320).

Angelucci, M., and G. De Giorgi. 2009. "Indirect Effects of an Aid Program: How Do Cash Transfers Affect Ineligibles' Consumption?" *The American Economic Review* no. 99 (1):486-508.

Baird, Sarah, Francisco Ferreira, Berk Özler, and Michael Woolcock. 2013. "Relative effectiveness of conditional and unconditional cash transfers for schooling outcomes in developing countries: a systematic review." *London: 3ie*.

Barrett, Christopher, Michael Carter, and Munenobu Ikegami. 2008. "Poverty traps and social protection." *Available at SSRN 1141881*.

Barrientos, Armando. 2012. "Social Transfers and Growth: What do we know? What do we need to find out?" *World Development* no. 40 (1):11-20.

Barrientos, Armando, and Rachel Sabatés-Wheeler. 2010. "Do transfers generate local economy effects?".

Caliendo, Marco, and Sabine Kopeinig. 2008. "Some practical guidance for the implementation of propensity score matching." *Journal of economic surveys* no. 22 (1):31-72.

Carter, Michael R, and Christopher B Barrett. 2006. "The economics of poverty traps and persistent poverty: An asset-based approach." *The Journal of Development Studies* no. 42 (2):178-199.

Davis, Benjamin, Marie Gaarder, Sudhanshu Handa, and Jenn Yablonski. 2012. "Evaluating the impact of cash transfer programmes in sub-Saharan Africa: an introduction to the special issue." *Journal of development effectiveness* no. 4 (1):1-8.

De Mel, S., D. McKenzie, and C. Woodruff. 2008. "Returns to capital in microenterprises: evidence from a field experiment." *The Quarterly Journal of Economics* no. 123 (4):1329-1372.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2012a. "Business training and female enterprise start-up, growth, and dynamics: experimental evidence from Sri Lanka."

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2012b. "One-time transfers of cash or capital have long-lasting effects on microenterprises in Sri Lanka." *Science* no. 335 (6071):962-966.

Deaton, A. 1990. Savings in developing countries: theory and review. Paper read at Proceedings of the World Bank annual conference on development economics 1989.

Del Ninno, Carlo , and Bradford Mills. 2014. *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*. Washington DC: World Bank.

Elbers, Chris, Jan Willem Gunning, and Bill Kinsey. 2007. "Growth and risk: Methodology and micro evidence." *The World Bank Economic Review* no. 21 (1):1-20.

Evans, David, and Manuel Salazar. 2011. Tanzania Community Based Conditional Cash Transfer Program. In *PowerPoint presentation*. Spanish Impact Evaluation Fund (SIEF).

Fafchamps, Marcel, David McKenzie, Simon Quinn, and Christopher Woodruff. 2014. "Microenterprise growth and the flypaper effect: Evidence from a randomized experiment in Ghana." *Journal of Development Economics* no. 106:211-226.

Fiala, Nathan. 2013. "Stimulating Microenterprise Growth: Short-term Results from a Loans, Grants and Training Experiment in Uganda."

Fiszbein, A., and N.R. Schady. 2009. *Conditional cash transfers: reducing present and future poverty*: World Bank Publications.

Garcia, Marito, and Charity MT Moore. 2012. *The Cash Dividend: The Rise of Cash Transfer Programs in Sub-Saharan Africa*. Washington, DC: The World Bank.

Gertler, P.J., S.W. Martinez, and M. Rubio-Codina. 2012. "Investing Cash Transfers to Raise Long-Term Living Standards." *American Economic Journal: Applied Economics* no. 4 (1):164-192.

Gilligan, Daniel, John Hoddinott, Neha Kumar, and Alemayehu Taffesse. 2009. "Can Social Protection work in Africa? Evidence on the impact of Ethiopia's Productive Safety Net Programme on food security, assets and incentives." *Evidence on the Impact of Ethiopia's Productive Safety Net Programme on Food Security, Assets and Incentives (August 18, 2009)*.

Gilligan, Daniel O, John Hoddinott, and Alemayehu Seyoum Taffesse. 2009. "The impact of Ethiopia's Productive Safety Net Programme and its linkages." *The journal of development studies* no. 45 (10):1684-1706.

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

Haushofer, Johannes, and Jeremy Shapiro. 2013. "Welfare Effects of Unconditional Cash Transfers: Evidence from a Randomized Controlled Trial in Kenya." *Unpublished Working Paper*.

Hoddinott, John, Guush Berhane, Daniel O Gilligan, Neha Kumar, and Alemayehu Seyoum Taffesse. 2012. "The Impact of Ethiopia's Productive Safety Net Programme and Related Transfers on Agricultural Productivity." *Journal of African Economies* no. 21 (5):761-786.

Hoddinott, John, Susanna Sandstrom, and Joanna Upton. 2013. The impact of cash and food transfers: Evidence from a randomized intervention in Niger. Paper read at 2013 Annual Meeting, August 4-6, 2013, Washington, DC.

Katayama, R. 2010. Appui à l'Equipe de Gestion dans le Cadre de la Mise en Œuvre du Projet Pilote des Filets Sociaux par le Transfert de Cash.

Lee, David S, and Thomas Lemieux. 2009. Regression discontinuity designs in economics. National Bureau of Economic Research.

Leuven, Edwin, and Barbara Sianesi. 2014. "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing." *Statistical Software Components*.

Macours, Karen, Patrick Premand, and Renos Vakis. 2012. "Transfers, Diversification and Household Risk Strategies: Experimental evidence with lessons for climate change adaptation." *World Bank Policy Research Working Paper* (6053).

Maina, Abdou. 2010. Projet Pilote des Filets Sociaux par le Cash Transfert, Situation de Référence. Niamey: CABINET DU PREMIER MINISTRE.

McBride. 2014. "Evaluation of Targeting Methods and Impact Of the Cash Transfer Pilot in Niger." In *Effective Targeting Mechanisms for the Poor and Vulnerable in Africa*, edited by C. Del Ninno and B. Mills. Washington, DC: World Bank.

McKenzie, David, and Christopher Woodruff. 2008. "Experimental evidence on returns to capital and access to finance in Mexico." *The World Bank Economic Review* no. 22 (3):457-482.

Miller, C., M. G. Tsoka, and K. Reichert. 2009. "The Impacts of the Cash Transfer on Children in Malawi." In *Social Protection for Africa's Children*, edited by S. Handa, S. Devereux and D. Webb. New York: UNICEF.

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

Olivier de Sardan, Jean-Pierre. 2013. Les transferts monétaires au Niger : la manne et les soupçons. Niamey: LASDEL.

Rosenbaum, Paul R, and Donald B Rubin. 1983. "The central role of the propensity score in observational studies for causal effects." *Biometrika* no. 70 (1):41-55.

Sabates-Wheeler, R., and S. Devereux. 2010. "Cash transfers and high food prices: Explaining outcomes on Ethiopia's Productive Safety Net Programme." *Food Policy* no. 35 (4):274-285.

Sadoulet, E., A. Janvry, and B. Davis. 2001. "Cash transfer programs with income multipliers: PROCAMPO in Mexico." *World Development* no. 29 (6):1043-1056.

Seidenfeld, D., and S. Handa. 2011. Results of the Three Year Impact Evaluation of Zambia's Cash Transfer Program in Monze District. American Institutes for Research.

Stoeffler, Q., and B. Mills. 2014. *Reaching the Poor: an Ex-Post Comparison of Targeting Mechanisms in Cameroon*.

Tembo, G, and N Freeland. 2009. Impact of social cash transfers on household welfare, investment and education in Zambia. In *Wahenga brief*.

Tumusiime, Emmanuel. 2013. "Does Early Cash-Based Interventions in a Food Crisis Enhance Resilience? Evidence from Niger."

Ward, Patrick, Alex Hurrell, Aly Visram, Nils Riemenschneider, Luca Pellerano, Clare O'Brien, Ian MacAuslan, and Jack Willis. 2010. Cash Transfer Programme for Orphans and Vulnerable Children (CT-OVC), Kenya. Oxford: Oxford Policy Management.

Figures

Figure 1: Eligibility status

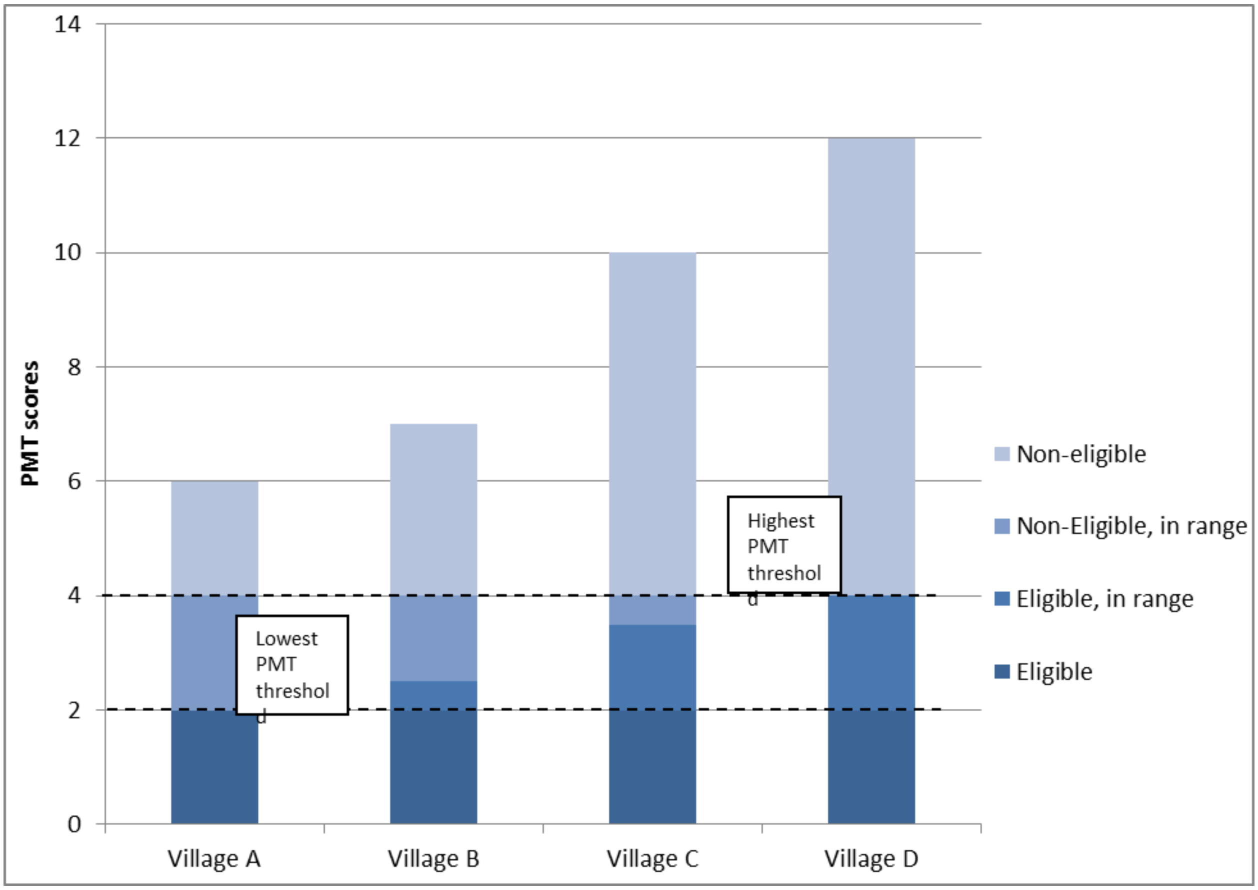
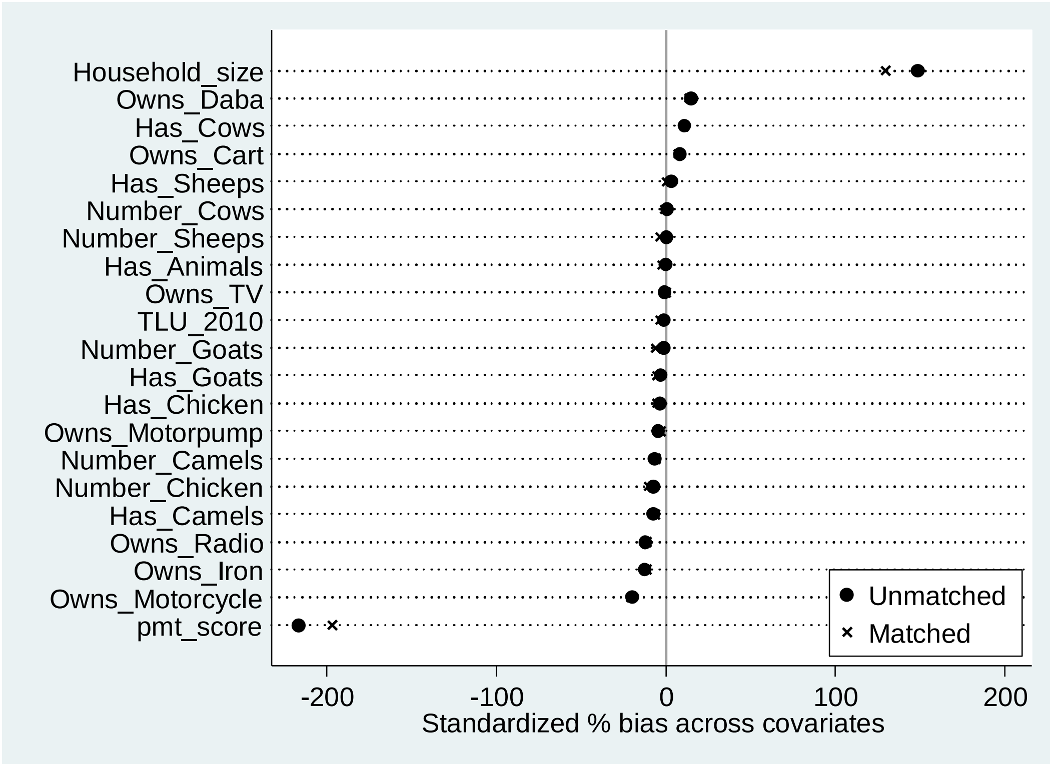


Figure 2: Propensity Score Matching estimator, test of balance



Note: test of balance for the PSM estimator for baseline (2010) variables.

Tables

Table 1: Descriptive Statistics, 2013 sample

	All	Non-Beneficiary	Beneficiary
Household size	8.16	6.49	9.63
Widow household head	0.028	0.028	0.027
Female household head	0.036	0.038	0.035
Handicapped household head	0.95	0.97	0.92
Household Dietary Diversity Score	5.25	5.11	5.38
PMT score	11,612.7	11,921.4	11,340.9
Adjusted PMT score	49.2	360.1	-224.5
Solid Walls	0.0076	0.0054	0.0096
Solid Roof	0.0076	0.013	0.0024
Access to clean water	0.30	0.29	0.31
Access to toilets	0.068	0.080	0.059
Home lighting	0.33	0.36	0.30
Cooking fuel	0.097	0.12	0.078
Different assets own (#)	6.52	6.30	6.72
Total value of assets (FCFA)	22,7938.9	26,3883.6	19,6074.0
Livestock (TLU)	1.16	0.90	1.39
Livestock in 2012 (TLU)	1.14	0.87	1.39
Livestock sales (FCFA)	20,785.6	14,066.4	26,742.1
Livestock consumption (FCFA)	9,987.3	7,687.3	12,026.2
Shock: any	0.64	0.63	0.65
Shock: loss of private transfers	0.023	0.015	0.030
Shock: theft	0.027	0.034	0.022
Shock: agriculture	0.58	0.58	0.58
Coping mechanism: any	0.25	0.25	0.24
Has tontine(s)	0.16	0.094	0.23
Number of tontines	0.20	0.11	0.28
Tontine amount (montly, FCFA)	363.6	122.1	577.8
Has Micro-Enterprise(s) (MEs)	0.13	0.12	0.14
Number of types of MEs	0.14	0.12	0.16
MEs revenues (monthly, FCFA)	5,335.8	3,427.2	7,027.8
MEs charges (monthly, FCFA)	3,039.6	2,689.9	3,349.7
MEs equipment total value	5.24	7.29	3.42
Total land	5.09	4.57	5.55
Total land owned	4.75	4.35	5.11
Total land borrowed	0.27	0.22	0.32
Uses fertilized	0.69	0.69	0.70
Total fertilizer spending	2,026.8	1,348.7	2,627.9
Total field spending	4,269.3	3,376.0	5,061.1
Number of crops	2.16	2.11	2.20
Quantity produced per hectare (kg)	164.8	155.1	173.2
Total quantity produced (kg)	616.0	532.7	689.8
Observations	1579	742	837

TLU = #camels *1+ #cows*0.7+(#sheeps+#goats)*0.1+(#chicken+#other poultry)*0.01+(#donkeys+#horses)*0.5

Table 2: Test of Attrition in PMT Range at Baseline (2010)

	All	Non-Attrition Households	Attrition Households	Difference p-value
Household size	7.88	7.94	7.54	(0.09)
# children (0-5)	1.38	1.40	1.24	(0.13)
Owns Iron	0.011	0.011	0.0068	(0.61)
Owns Radio	0.035	0.031	0.061	(0.07)
Owns TV	0.0043	0.0051	0	(0.38)
Owns Motorcycle	0.0086	0.0089	0.0068	(0.79)
Owns Daba (hoe)	0.95	0.95	0.95	(0.93)
Owns Motor-pump	0.019	0.019	0.020	(0.93)
Owns Fridge	0	0	0	-
Owns Cart	0.10	0.12	0.041	**(0.01)**
Has Cows	0.22	0.22	0.21	(0.74)
Has Sheeps	0.34	0.35	0.28	(0.09)
Has Goats	0.27	0.27	0.28	(0.69)
Has Camels	0.021	0.022	0.020	(0.91)
Has Chicken	0.24	0.25	0.20	(0.20)
# Cows	0.57	0.54	0.72	(0.26)
# Sheeps	0.89	0.90	0.83	(0.66)
# Goats	0.88	0.86	0.99	(0.47)
# Camels	0.038	0.043	0.0068	(0.29)
# Chicken	0.81	0.83	0.69	(0.44)
Tropical Livestock Unit	0.62	0.61	0.70	(0.51)
PMT score	11624.7	11618.8	11655.6	**(0.02)**
Adjusted PMT score	11.5	6.69	37.0	(0.09)
Observations	932	784	148	

Mean coefficients; p-values in parentheses. Bold indicates significance.
The Tropical Livestock Unit formula used is:
$TLU = \#camels * 1 + \#cows * 0.7 + (\#sheeps + \#goats) * 0.1 + (\#chicken + \#other\ poultry) * 0.01 + (\#donkeys + \#horses) * 0.5$

Table 3: Test of Balance in PMT Range at Baseline (2010)				
	All	Non-Beneficiary	Beneficiary	Difference p-value
Household size	7.89	6.64	8.83	**(0.00)**
# children (0-5)	1.38	1.11	1.58	**(0.00)**
Owns Iron	0.012	0.015	0.0093	(0.45)
Owns Radio	0.036	0.039	0.033	(0.64)
Owns TV	0.0042	0.0024	0.0056	(0.46)
Owns Motorcycle	0.0084	0.020	0	**(0.00)**
Owns Daba (hoe)	0.95	0.94	0.96	(0.15)
Owns Motor-pump	0.023	0.0098	0.033	**(0.02)**
Owns Fridge	0.0011	0	0.0019	(0.38)
Owns Cart	0.10	0.098	0.11	(0.61)
Has Cows	0.22	0.21	0.22	(0.72)
Has Sheeps	0.34	0.35	0.32	(0.39)
Has Goats	0.27	0.29	0.25	(0.13)
Has Camels	0.021	0.024	0.019	(0.54)
Has Chicken	0.24	0.25	0.24	(0.91)
# Cows	0.57	0.60	0.54	(0.61)
# Sheeps	0.88	0.96	0.81	(0.17)
# Goats	0.87	1.02	0.76	**(0.05)**
# Camels	0.037	0.054	0.024	(0.24)
# Chicken	0.80	0.89	0.73	(0.23)
Tropical Livestock Unit	0.62	0.68	0.57	(0.26)
PMT_score	11,627.2	11,756.5	11,528.8	**(0.00)**
Adjusted PMT score	8.21	194.4	-133.4	**(0.00)**
Observations	949	410	539	949

Mean coefficients; *p*-values in parentheses. Bold indicates significance.
The Tropical Livestock Unit formula used is:

$$\text{TLU} = \#camels * 1 + \#cows * 0.7 + (\#sheeps + \#goats) * 0.1 + (\#chicken + \#other\ poultry) * 0.01 + (\#donkeys + \#horses) * 0.5$$

Table 4: Simple Difference Results: Tontines						
	(1) Simple Difference, Basic model		(2) Simple Difference, Errors Clustered at the Village level		(3) Simple Difference, Village Dummies	
	“Beneficiary” Coefficient	Standard Errors	“Beneficiary” Coefficient	Standard Errors	“Beneficiary” Coefficient	Standard Errors
Has tontine(s)	**0.080*****	(0.026)	**0.080*****	(0.029)	**0.087*****	(0.030)
Number of tontines	**0.085****	(0.038)	**0.085****	(0.036)	**0.101*****	(0.031)
Tontine amount invested (montly, FCFA)	**376.179***	(203.736)	**376.179****	(186.807)	**447.383***	(229.817)
Tontine amount received (ponctual, FCFA)	**2,797.609*****	(953.101)	**2,797.609*****	(949.105)	**3,906.961****	(1,636.218)
Log of tontine amount invested (montly, FCFA)	**0.609*****	(0.182)	**0.609*****	(0.207)	**0.664*****	(0.218)
Log of tontine amount received (ponctual, FCFA)	**0.785*****	(0.230)	**0.785*****	(0.262)	**0.886*****	(0.280)
Tontine usage: consumption	**0.056*****	(0.020)	**0.056*****	(0.020)	**0.067*****	(0.022)
Tontine usage: productive investment	**0.037*****	(0.014)	**0.037****	(0.016)	**0.035***	(0.019)
Tontine usage: private investment	**0.014***	(0.008)	**0.014****	(0.006)	**0.018****	(0.009)
Tontine usage: other	**0.031****	(0.014)	**0.031****	(0.014)	**0.047*****	(0.017)

Notes: Observations: 784 households.

Table 5: Simple Difference Results: Investments

	(1) Simple Difference, Basic model		(2) Simple Difference, Errors Clustered at the Village level		(3) Simple Difference, Village Dummies	
Panel A: Housing						
	"Beneficiary" Coefficient	Standard Errors	"Beneficiary" Coefficient	Standard Errors	"Beneficiary" Coefficient	Standard Errors
Aggregate index of housing quality	0.023	(0.058)	0.023	(0.073)	-0.020	(0.060)
Solid Walls	0.007	(0.007)	**0.007***	(0.004)	-0.003	(0.004)
Solid Roof	-0.001	(0.004)	-0.001	(0.004)	-0.001	(0.004)
Access to clean water	**0.063***	(0.033)	0.063	(0.043)	0.024	(0.030)
Access to toilets	**0.041***	(0.024)	0.041	(0.027)	-0.005	(0.019)
Home lighting	-0.049	(0.033)	-0.049	(0.038)	-0.025	(0.030)
Cooking fuel	0.019	(0.021)	0.019	(0.037)	0.006	(0.028)
Panel B: Physical Assets						
# of different assets own	**0.279***	(0.152)	**0.279***	(0.163)	0.275	(0.168)
# of different assets purchased, last 3 years	-0.047	(0.140)	-0.047	(0.138)	-0.032	(0.152)
Total value of assets (FCFA)	-243,875	(251,888)	-243,875	(298,595)	-325,673	(378,684)
Assets purchased, last 3 years (FCFA)	**19,292****	(8,241)	**19,292****	(8,757)	**21,553****	(10,618)
Log of total value of assets (FCFA)	**0.305*****	(0.092)	**0.305*****	(0.095)	**0.271*****	(0.097)
Log of assets purchased, last 3 years (FCFA)	**0.246***	(0.130)	**0.246***	(0.142)	0.236	(0.146)
Panel C: Livestock						
Livestock (TLU)	**0.295*****	(0.106)	**0.295*****	(0.077)	**0.286*****	(0.077)
Livestock in 2012 (in TLU)	**0.312****	(0.128)	**0.312*****	(0.091)	**0.308*****	(0.098)
Value of livestock (FCFA)	**62,360.759*****	(18,919.485)	**62,360.759*****	(14,342.684)	**55,299.655*****	(14,688.627)
Value of livestock sales (FCFA)	2,755.309	(5,676.500)	2,755.309	(3,880.446)	**8,884.269****	(4,405.824)
Value of livestock consumption (FCFA)	**4,261.585***	(2,235.016)	**4,261.585****	(1,706.855)	**3,147.724***	(1,671.783)
Log of value of livestock (FCFA)	**0.702****	(0.351)	**0.702****	(0.339)	**0.867****	(0.363)
Log of livestock sales	-0.211	(0.316)	-0.211	(0.384)	0.452	(0.392)

(FCFA)						
Log of livestock consumption (FCFA)	**0.822*** **	(0.309)	**0.822** **	(0.336)	**0.584***	(0.340)
Livestock difference: 2013 - 2012 (TLU)	0.012	(0.057)	0.012	(0.045)	0.004	(0.057)
Panel D: Micro-Enterprises (ME)						
Has ME(s)	0.015	(0.025)	0.015	(0.030)	0.013	(0.032)
Number of types of ME	0.028	(0.027)	0.028	(0.031)	0.025	(0.032)
Has ME type: transportation	**0.013** **	(0.006)	**0.013*** **	(0.005)	**0.014** **	(0.006)
ME created, last 3 years	0.017	(0.016)	0.017	(0.012)	0.019	(0.014)
ME(s) revenues (monthly, FCFA)	6,335.662	(5,431.992)	6,335.662	(4,561.961)	11.735	(1,098.065)
ME(s) charges (monthly, FCFA)	3,678.288	(3,114.931)	3,678.288	(2,738.846)	-16.639	(544.745)
ME(s) profits (monthly, FCFA)	2,652.988	(5,124.771)	2,652.988	(1,978.102)	22.644	(820.029)
ME equipment total value	1.686	(1.341)	1.686	(1.049)	1.964	(1.548)
ME equipment purchased, last 3 years	**0.023***	(0.013)	**0.023** **	(0.010)	**0.019***	(0.011)
Panel E: Agriculture						
Total land	-0.240	(0.325)	-0.240	(0.355)	0.302	(0.312)
Total land owned	**-0.544***	(0.325)	-0.544	(0.357)	0.131	(0.301)
Total land borrowed	**0.213** **	(0.104)	**0.213***	(0.111)	0.127	(0.104)
Uses fertilized	**-0.063***	(0.032)	**-0.063***	(0.035)	-0.007	(0.030)
Total fertilizer spending (FCFA)	**2,362.968** **	(1,085.080)	**2,362.968***	(1,297.166)	**1,040.473***	(557.235)
Total field spending (FCFA)	1,881.400	(1,292.853)	1,881.400	(1,457.967)	1,133.570	(738.918)
Number of crops	0.068	(0.050)	0.068	(0.043)	**0.073***	(0.039)
Quantity produced per hectare (kg)	**31.095*** **	(10.908)	**31.095** **	(12.687)	**21.855***	(11.617)
Total quantity produced (kg)	**68.915***	(40.466)	**68.915***	(40.966)	**111.862*** **	(42.936)

Notes: Observations: 784 households. The Tropical Livestock Unit formula used is:

$TLU = \#camels * 1 + \#cows * 0.7 + (\#sheeps + \#goats) * 0.1 + (\#chicken + \#other\ poultry) * 0.01 + (\#donkeys + \#horses) * 0.5$

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

Table 6: Simple Difference Results: Shocks						
	(1) Simple Difference, Basic model		(2) Simple Difference, Errors Clustered at the Village level		(3) Simple Difference, Village Dummies	
	“Beneficiary” Coefficient	Standard Errors	“Beneficiary” Coefficient	Standard Errors	“Beneficiary” Coefficient	Standard Errors
Shock: any	0.027	(0.034)	0.027	(0.037)	0.008	(0.029)
Shock: loss of private transfers	**0.019****	(0.008)	**0.019****	(0.009)	**0.020***	(0.011)
Shock: theft	**-0.036*****	(0.014)	**-0.036****	(0.014)	**-0.024***	(0.014)
Shock: agriculture	0.028	(0.035)	0.028	(0.044)	-0.010	(0.036)
Coping mechanism: nothing	**0.063***	(0.036)	0.063	(0.042)	-0.032	(0.032)
Coping mechanism: any	**-0.072****	(0.032)	**-0.072****	(0.030)	0.040	(0.029)
Coping mechanism: cash spending	-0.018	(0.023)	-0.018	(0.027)	0.029	(0.028)
Coping mechanism: sale of assets	-0.012	(0.016)	-0.012	(0.020)	0.008	(0.018)
Coping mechanism: other	**-0.055****	(0.024)	**-0.055****	(0.022)	0.002	(0.025)

Notes: Observations: 784 households.

Table 7: DID model

	(1) Index of housing quality	(2) Cooking fuel	(3) Access to clean water	(4) Home lighting	(5) Access to toilets	(6) Different assets own (#)	(7) Livestock (TLU)
2013	0.0366	-0.0335	0.204**	-0.244***	0.0152	0.613***	-0.0207
	(0.16)	(-1.16)	(2.43)	(-4.42)	(0.53)	(6.26)	(-0.16)
Beneficiary	-0.0540	0.0186	0.0633	-0.0487	-0.0165	0.118	-0.0671
	(-0.40)	(0.50)	(1.49)	(-1.29)	(-0.85)	(1.31)	(-0.54)
2013 * Beneficiary	**0.0358**	**-0.0279**	**-0.0683**	**0.0553**	**0.0571*****	**-0.0119**	**0.363****
	(0.21)	**(-0.77)**	**(-1.23)**	**(1.48)**	**(1.71)**	**(-0.11)**	**(2.59)**
Constant	2.052***	0.0823***	0.274***	0.314***	0.0823***	4.320***	0.648***
	(13.39)	(3.18)	(4.81)	(6.34)	(3.59)	(53.54)	(5.22)
Observations	1568	1568	1568	1568	1568	1568	1568

t statistics in parentheses
Standard Errors are clustered at the village level. The Tropical Livestock Unit formula used is: TLU = #camels * 1 + #cows * 0.7 + (#sheeps + #goats) * 0.1 + (#chicken + #other poultry) * 0.01 + (#donkeys + #horses) * 0.5. Bold indicates the DID estimator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regression Discontinuity Design Results						
	(1) Iwald (default bandwidth)		**(2) Iwald (default bandwidth * 0.5)**		**(3) Iwald (default bandwidth * 2)**	
Aggregate index of housing quality	-0.952	(0.873)	-0.500	(0.657)	0.025	(0.763)
Access to clean water	**-0.552*****	(0.192)	(dropped)		0.176	(0.261)
Access to toilets	-0.000	(0.000)	(dropped)		-0.000	(0.000)
Home lighting	0.017	(0.140)	**0.000****	(0.000)	0.304	(0.299)
Cooking fuel	-0.750	(1.003)	(dropped)		-0.584	(0.614)
Number of different assets own	**7.943*****	(2.881)	**8.063***	(4.676)	**6.230*****	(1.762)
Number of different assets purchased in the last 3 years	3.735	(3.991)	5.250	(5.051)	**3.859***	(2.166)
Total value of assets (USD)	-347.460	(968.178)	243.274	(151.857)	-3,735.744	(3,618.542)
Total value of assets purchased in the last 3 years (USD)	45.762	(117.155)	138.816	(101.717)	185.621	(160.172)
Livestock (TLU)	-1.428	(2.527)	**1.135*****	(0.151)	-0.470	(1.876)
Livestock in 2012 (TLU)	-0.797	(2.060)	-1.374	(3.346)	-0.032	(1.472)
Value of livestock sales (USD)	101.148	(66.391)	166.493	(101.650)	**85.827***	(47.204)
Value of livestock consumption (USD)	8.649	(16.817)	-28.219	(24.681)	6.417	(20.090)
Shock: any	**1.377***	(0.819)	0.500	(0.664)	**0.758***	(0.445)
Shock: loss of private transfers	(dropped)		(dropped)		(dropped)	
Shock: theft	0.000	(0.000)	0.000		-0.000	(0.000)
Shock: agriculture	**1.378***	(0.816)	0.500	(0.664)	**0.731***	(0.442)
Coping mechanism: nothing	-0.005	(0.205)	0.000	(0.000)	0.058	(0.079)
Coping mechanism: any	**1.370***	(0.795)	(dropped)		0.712	(0.434)
Coping mechanism: cash spending	1.250	(1.003)	(dropped)		0.915	(0.627)
Coping mechanism: sale of assets	(dropped)		(dropped)		0.393	(0.470)
Coping mechanism: other	-0.000	(0.000)	0.000	(0.000)	-0.039	(0.072)
Has tontine(s)	**0.843***	(0.511)	0.725	(0.553)	**0.918****	(0.402)
Number of tontines	**0.851***	(0.447)	0.723	(0.553)	**0.909****	(0.369)
Tontine amount (montly, FCFA)	522.968	(443.534)	1,097.833	(958.128)	272.475	(246.577)
Tontine usage: consumption	0.840	(0.513)	0.725	(0.553)	**0.919****	(0.404)
Tontine usage: productive investment	0.200	(0.569)	0.273	(0.658)	0.403	(0.382)
Tontine usage: private investment	(dropped)		(dropped)		0.686	(0.726)
Tontine usage: other	0.756	(0.498)	0.726	(0.554)	0.671	(0.436)
Has ME(s)	0.397	(0.468)	0.000	(0.000)	**0.491*****	(0.082)
Number of types of ME	0.665	(0.823)	(dropped)		**0.567*****	(0.209)

ME created (the last 3 years)	0.283	(0.495)	(dropped)		0.038	(0.096)
ME(s) revenues (monthly, FCFA)	-4,561.563	(6,004.664)	-9,121.722	(6,496.578)	-9,560.981	(6,181.285)
ME(s) charges (monthly, FCFA)	-3,886.571	(4,906.437)	-6,510.161	(4,939.100)	-4,425.742	(3,422.584)
ME(s) profits (monthly, FCFA)	1,098.002	(4,307.590)	-2,192.680	(1,433.788)	-5,126.499	(3,242.651)
ME equipment total value	0.224	(0.342)	-0.578	(1.505)	0.736	(0.765)
ME equipment purchased (last 3 years)	-0.316	(0.451)	0.000	(0.000)	-0.055	(0.101)
Total land	0.889	(2.828)	-0.200	(3.412)	0.202	(1.778)
Total land owned	1.176	(2.866)	0.362	(3.429)	0.450	(1.676)
Total land borrowed	-0.288	(0.602)	(dropped)		0.063	(0.136)
Uses fertilized	-0.163	(0.540)	-0.275	(0.553)	-0.187	(0.404)
Total fertilizer spending (FCFA)	**1,583.549***	(962.163)	218.405	(1,049.886)	**1,426.713****	(701.360)
Total field spending (FCFA)	**3,863.749****	(1,768.716)	855.071	(1,189.173)	-219.788	(2,267.315)
Number of crops	1.565	(1.559)	0.901	(1.257)	0.764	(0.819)
Quantity produced per hectare (kg)	11.048	(54.499)	**-57.297***	(31.986)	25.754	(36.544)
Total quantity produced (kg)	95.791	(253.060)	-231.457	(321.917)	256.065	(156.632)

Standard Errors in parentheses.
Observations: 1553 households. The Tropical Livestock formula used is: TLU = #camels * 1 + #cows * 0.7 + (#sheeps + #goats) * 0.1 + (#chicken + #other poultry) * 0.01 + (#donkeys + #horses) * 0.5. Bold indicates the DID estimator.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Propensity Score Matching estimators

	Average Treatment Effect on the Treated (ATT)	
Aggregate index of housing quality	**-0.126*** **	(0.041)
Access to clean water	0.013	(0.023)
Access to toilets	-0.019	(0.013)
Home lighting	**-0.071*** **	(0.024)
Cooking fuel	**-0.039*** **	(0.015)
Number of different assets own	**0.410*** **	(0.111)
Number of different assets purchased in the last 3 years	**0.242** **	(0.102)
Total value of assets (FCFA)	-68,080.843	(125,918.726)
Total value of assets purchased in the last 3 years (FCFA)	**25,353.787*** **	(6,087.865)
Livestock (TLU)	**0.475*** **	(0.081)
Livestock in 2012 (TLU)	**0.514*** **	(0.092)
Value of livestock sales (FCFA)	**12,772.135*** **	**12,772.135*** **
Value of livestock consumption (FCFA)	**4,403.817*** **	**4,403.817*** **
Shock: any	0.013	(0.024)
Shock: loss of private transfers	**0.015** **	(0.008)
Shock: theft	-0.012	(0.008)
Shock: agriculture	-0.005	(0.025)
Coping mechanism: nothing	0.024	(0.025)
Coping mechanism: any	-0.010	(0.022)
Coping mechanism: cash spending	0.003	(0.016)
Coping mechanism: sale of assets	-0.001	(0.011)
Coping mechanism: other	-0.017	(0.016)
Has tontine(s)	**0.135*** **	(0.018)
Number of tontines	**0.164*** **	(0.027)
Tontine amount (montly, FCFA)	**466.974*** **	(125.789)
Tontine usage: consumption	**0.105*** **	(0.015)
Tontine usage: productive investment	**0.077*** **	(0.012)
Tontine usage: private investment	**0.019*** **	(0.006)
Tontine usage: other	**0.071*** **	(0.011)
Has ME(s)	0.022	(0.017)
Number of types of ME	**0.034* **	(0.019)
ME created (the last 3 years)	0.007	(0.011)
ME(s) revenues (monthly, FCFA)	3,688.613	(2,930.713)
ME(s) charges (monthly, FCFA)	657.609	(2,003.616)
ME(s) profits (monthly, FCFA)	3,041.531	(2,867.565)
ME equipment total value	-3.906	(4.528)
ME equipment purchased (last 3 years)	0.013	(0.009)

Total land	**0.962*** **	(0.244)
Total land owned	**0.749*** **	(0.244)
Total land borrowed	0.099	(0.062)
Uses fertilized	0.005	(0.023)
Total fertilizer spending (FCFA)	**1,358.365** **	(619.772)
Total field spending (FCFA)	1,669.798	(1,062.384)
Number of crops	**0.092** **	(0.037)
Quantity produced per hectare (kg)	**19.364** **	(7.910)
Total quantity produced (kg)	**160.160*** **	(32.260)

Standard Errors in parentheses. Bold indicates statistical significance.
Observations: 1553 households. The Tropical Livestock formula used is: TLU = #camels * 1 + #cows * 0.7 + (#sheeps + #goats) * 0.1 + (#chicken + #other poultry) * 0.01 + (#donkeys + #horses) * 0.5. Bold indicates the DID estimator.
* p < 0.10, ** p < 0.05, *** p < 0.01

CONCLUSION

This dissertation has been concerned with the broad topic of poverty in SSA, each of its essays delving into a key component of the poverty alleviation process: poverty definition and measurement; poor households targeting for poverty alleviation interventions; and impact evaluation of poverty alleviation interventions. The three papers analyze how risks and shocks (at the national and household levels) affect individual well-being, and examine what types of methods and interventions can help reduce ex-post risk and cope with ex-post shocks, while facilitating effective poverty alleviation strategies.

The first essay studied multidimensional poverty changes in Zimbabwe before, during and after the peak of the hyperinflation crisis in 2007-2008. It shows that multidimensional poverty unambiguously increased in Zimbabwe from 2001 to 2007, and then decreased from 2007 to 2011/12 during the economic recovery. These results suggest that multidimensional well-being is fluid in times of crisis: long-term dimensions of well-being that are normally viewed as relatively fixed in the short to medium term changed rapidly in Zimbabwe. Further, changes in well-being vary across different dimensions of poverty, illustrating the need to aggregate deprivations in a meaningful index and to also carefully examine the underlying components. The results also suggest that social assistance programs need to address both the acute effect of the crisis when it happens and provide continued assist poor households along slowly recovering dimensions in the longer-term, while at the same time building resilience to future shocks.

The second essay analyzes the efficiency of two targeting mechanisms, community-based targeting (CBT) and PMT, employed in a pilot unconditional cash transfer pilot project in

Northern Cameroon. Results are not very encouraging for community targeting when per capita consumption is used to define poverty. PMT targeting outperforms both community and hybrid targeting, but its exclusion and inclusion errors also remain high when it selects 35% of the households as beneficiaries. Further, PMT is not clearly superior to the simulated impact of universal transfers with equal budget. Importantly, the analysis of community errors and drivers suggest that communities have a different conception of poverty than per capita consumption only. However, community targeting produces very variable outcomes on observationally similar households even with other definitions of poverty. These findings suggest a need for: better guidance and supervision for community targeting; further investments in targeting systems in general; and further research on the drivers and the efficiency of community targeting in generating beneficiaries involvement and satisfaction.

The third essay is an ex-post impact evaluation of a similar unconditional cash transfer in rural Niger, 18 months after project termination. The essay investigates the long-term effect of project transfers by measuring how beneficiary households invested in durable assets, using quasi-experimental methods. Results show that households have increased their livestock by half a cow on average (or equivalently, three goats or thirty chicken), which is more than half of their baseline stock (in TLU). Beneficiary improvements can also be related to a higher participation to local saving and credit systems (tontines) compared to non-beneficiaries. Similar impacts are found on other assets and agricultural activities. These findings indicate the potential for cash transfers to stimulate investment even in poor rural households which, because of multiple constraints, are not necessarily expected to take advantage of the cash transfers to realize medium-term investments and accumulate assets.

Overall, the three essays also raise many questions. The definition of poverty is central to each of them, in order to construct a multidimensional index to quantify poverty changes in Zimbabwe, assess community targeting rigorously in Cameroon, and interpret the increase in productive assets in Niger. Also, each essay is only a snapshot of a particular situation, limited by the data at hand and by the empirical realities of the study: What would have been the evolution of poverty in Zimbabwe in the absence of crisis? How would have community targeting performed in Cameroon at a different level of selection or with better guidance and supervision? What would have been the productive impact of the transfers in Niger with different levels of transfers or program duration? This dissertation calls for further research in these crucial areas.

Appendix A: IRB permission letter

VirginiaTech

Office of Research Compliance
Institutational Review Board
2000 Kraft Drive, Suite 2000 (0497)
Blacksburg, VA 24060
540/231-4606 Fax 540/231-0959
email irb@vt.edu
website http://www.irb.vt.edu

MEMORANDUM

DATE:	August 29, 2012
TO:	Bradford F Mills Jr, Quentin Stoeffler
FROM:	Virginia Tech Institutional Review Board (FWA00000572, expires May 31, 2014)
PROTOCOL TITLE:	IMPLEMENTATION OF SAFETY NET PROGRAMS IN CAMEROON
IRB NUMBER:	**12-703**

Effective August 29, 2012, the Virginia Tech Institution Review Board (IRB) Chair, David M Moore, approved the New Application request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

http://www.irb.vt.edu/pages/responsibilities.htm

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As:	**Exempt, under 45 CFR 46.110 category(ies) 2**
Protocol Approval Date:	**August 29, 2012**
Protocol Expiration Date:	**N/A**
Continuing Review Due Date*:	**N/A**

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

FEDERALLY FUNDED RESEARCH REQUIREMENTS:

Per federal regulations, 45 CFR 46.103(f), the IRB is required to compare all federally funded grant proposals/work statements to the IRB protocol(s) which cover the human research activities included in the proposal / work statement before funds are released. Note that this requirement does not apply to Exempt and Interim IRB protocols, or grants for which VT is not the primary awardee.

The table on the following page indicates whether grant proposals are related to this IRB protocol, and which of the listed proposals, if any, have been compared to this IRB protocol, if required.

Invent the Future

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
An equal opportunity, affirmative action institution

Date*	OSP Number	Sponsor	Grant Comparison Conducted?
08/29/2012	13022107	The World Bank	Not required (Not federally funded)

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this IRB protocol is to cover any other grant proposals, please contact the IRB office (irbadmin@vt.edu) immediately.