

## How to Target Households in Adaptive Social Protection Systems? Relative Efficiency of Proxy Means Test and Household Economy Analysis in Niger

Pascale Schnitzer



October 2016

# How to Target Households in Adaptive Social Protection Systems? Relative Efficiency of Proxy Means Test and Household Economy Analysis in Niger<sup>1</sup>

August 2016

Pascale Schnitzer

## Abstract

Proxy Means Test (PMT) and the Household Economy Analysis (HEA) are widely used methods to target chronically poor households and those suffering from food crises respectively. Using panel data from Niger, this study provides the first empirical evidence on the relative efficiency of these methods in identifying households suffering from permanent or seasonal deprivations. Results show limited overlap between households selected by each method. The PMT performs better in targeting chronically poor households, while HEA performs better in targeting seasonal food insecure households. The study also explores the extent to which these methods can be improved, used and potentially combined to target households as part of ASP systems. Results show that the HEA formula could be further improved to target seasonally food insecure households, including through a regression model estimating food insecurity, and a principal component analysis (PCA) model. Combinations of PMT with methods such as HEA, PCA, or a food insecurity formula may be considered to identify households suffering from chronic poverty and seasonal food insecurity as part of an efficient and scalable ASP system. Harmonizing data collection tools of PMT and HEA users would serve as a crucial building block towards a unified registry and play a key role in improving the efficiency of ASP systems.

**Keywords:** Poverty, cash transfers, means test, targeting, Africa, adaptive social protection

**JEL:** I32, I38

---

<sup>1</sup> Acknowledgments: I thank Carlo del Ninno, Patrick Premand, Bradford Mills, Quentin Stoeffler, Arthur Alik, Phillippe Leite, Leila Bourahla, Marie Boulinaud, and Julius Gunnemann for very valuable inputs and comments on the manuscript. Participants to workshops that took place in Washington, DC and Niger also provided useful comments. They included the Food Economy Group (FEG) as well as different non-governmental organizations making use of the Household Economy Analysis. The research and the compilation of this work would not have been possible without the generous contribution from the Adaptive Social Protection Program for the Sahel Multi-donor Trust Fund, funded by the United Kingdom.

## Content

1. Background and objectives .....	1
2. Description and literature of PMT and HEA methods.....	3
2.1 PMT: Description and literature.....	3
2.2 HEA: Description and literature.....	5
2.3 PMT and HEA methods used in Niger.....	6
3. Data .....	8
4. Methodology .....	9
4.1 Simulating PMT and HEA selection of beneficiaries.....	9
4.2 Welfare benchmarks, vulnerability and targeting errors - concepts and definitions .....	11
5. Descriptive statistics on consumption per capita and the FCS .....	14
6. Households targeted under the PMT and HEA methods .....	17
6.1 Overlap between HEA and PMT .....	17
6.2 Targeting efficiency .....	18
6.3 Characterizing households under each method .....	21
7. Can the design of formulas be improved? .....	23
7.1 Design of HEA .....	23
7.2 Adjusting consumption for economies of scale and adult equivalent .....	26
8. How can the existing methods be used in the context of ASP systems? .....	28
8.1 Combining PMT and HEA to get the best out of each method .....	28
8.2 Harmonize data collection tools applied by PMT and HEA users.....	29
9. Conclusion and policy implications .....	30
References.....	34
Annex 1: Comparability of ECVM/A data with the HEA variables used for targeting .....	37
Annex 2: Tables .....	39

## Tables

Table 1: General characteristics of PMT and HEA households .....	23
Table 2: Inclusion errors of quantitative methods aiming to replicate HEA .....	26
Table 3: PMT inclusion errors when adjusting for household composition.....	27
Table 4: Inclusion errors for current programs and scenarios 1 and 2. ....	29

## Figures

Figure 1: Chronic and transitory poverty and food insecurity .....	15
Figure 2: Percentage change in welfare measures between the lean and harvest season .....	16
Figure 3: Correlations between welfare measures .....	17
Figure 4: Overlap between beneficiaries at different cut-off points .....	18
Figure 5: Inclusion error based on consumption and FCS - Selection of 30% of households .....	19
Figure 6: Rates of chronic and seasonal poor and food insecure among PMT and HEA selected households .....	20
Figure 7: Share of targeted households that are “deprived” based on different metrics .....	21

## Annex tables

Table A1: Food insecurity by season .....	39
Table A2: Poverty by season.....	39
Table A3: Percentage change in welfare measures between the lean and harvest season .....	40
Table A4: Correlations between welfare measures .....	40
Table A5: Overlap between beneficiaries when selecting different shares of households.....	41
Table A6: PMT and HEA inclusion errors based on different welfare measures .....	41
Table A7: PMT performance based on temporary and chronic poverty and food insecurity .....	42
Table A8: HEA performance based on temporary and chronic poverty and food insecurity .....	42
Table A9: Share of targeted households that are “deprived” based on different welfare measures .	43
Table A10: Differences in livelihood diversification between PMT and HEA households .....	43
Table A11: Differences in livelihoods between PMT and HEA households.....	44

## 1. Background and objectives

Adaptive Social Protection (ASP) systems are increasingly popular as an instrument to reduce poverty and mitigate the impact of shocks. Poor and vulnerable people in developing countries are facing ever greater and deeper shocks to their livelihoods. These include climatic shocks, such as floods and droughts, as well as other financial, price, food or fuel related stresses. With climate change, the magnitude and frequency of climate related shocks is expected to increase, disproportionately affecting the poor<sup>2</sup>. Reliance on subsistence agriculture means the impact of shocks (such as droughts or floods) are felt most strongly by rural poor people, whose survival often depends directly on food system outcomes. These stresses make it increasingly difficult for poor people's usual coping strategies to effectively protect their livelihoods from shocks with often long lasting implications for their wellbeing.

Interventions in the fields of Social Protection, Climate Change Adaptation and Disaster Risk Reduction all aim to reduce vulnerability to shocks. Adaptive Social Protection (ASP) recognizes that greater integration and knowledge sharing among these three fields would improve the effectiveness of interventions aimed at reducing vulnerability to shocks (Davies et al 2013).

ASP follows a two-fold approach to mitigate the impact of shocks and to reduce poverty. First, it builds resilience before shocks occur (through predictable transfers, building community assets, and other programs that promote resilience). Second, it quickly scales up safety nets in response to shocks.

Effectively identifying households that are poor and vulnerable to poverty is a critical aspect of ASP to maximize social impact with scarce resources. Yet, limited evidence exist on methods that can identify both population groups. Using household panel data from Niger, this study compares the effectiveness of Household Economy Analysis (HEA) and Proxy Means Test (PMT) targeting methods in Niger. The HEA targeting method used in Niger was

---

<sup>2</sup> Without appropriate interventions climate change could force more than 100 million people into extreme poverty by 2030 (Hallegatte et al. 2016).

specifically developed to identify food insecure households in response to crises (with no specific measurable welfare defined). By contrast, the PMT in Niger was developed to target households that are chronically poor, i.e. those with low consumption per capita.

This study aims to address the following key questions:

1. What is the overlap between households selected under the PMT and HEA method?
2. What is the relative efficiency of the PMT and HEA based on key welfare benchmarks?
3. How can the methods be improved?
4. How can the existing methods be used in the context of an ASP systems in Niger?

This study focuses on the efficiency of the targeting methods in identifying two groups: (1) households with low consumption per capita—as a measure of poverty; and (2) household with a low Food Consumption Score (FCS) during the lean season—as a measure of food insecurity. To investigate the performance of methods based on other dimensions of household well-being, the analysis also looks at alternative metrics such as income, non-productive assets, livestock and land.

Results show that PMT and HEA target two largely different types of population and that the performance of each method depends on the welfare indicator used. PMT performs better in targeting chronically poor households (measured by consumption per capita during both the lean and harvest season), while HEA performs better in targeting seasonal food insecure households (measured through the Food Consumption Score during the lean season). PMT selected households consume less calories per capita, are relatively larger and are asset poor but have, more diversified livelihoods. HEA selected households are relatively smaller, have lower levels of livestock, less land and less diversified livelihoods. Key challenges in the implementation of the HEA method are discussed and solutions are presented. Finally, the study shows that a combination of the PMT and HEA method could be used effectively to address the targeting needs of ASP systems.

This study is organized as follows. Section 2 describes the PMT and HEA methods and links those to the existing literature. Sections 3 and 4 describe the data and methodology, respectively. Section 6, 7 and 8 discuss results and Section 9 presents the policy implications and conclusion.

## 2. Description and literature of PMT and HEA methods

Targeting households is difficult because the criteria for eligibility is hard to measure and verify. Measuring household expenditures—the most widely used indicator of poverty in low income settings—not only relies on long and expensive survey modules but also remains difficult to verify. This is a major concern in the context of cash transfer programs when households may have an incentive to strategically under report their well-being to gain access to programs.

The challenges of measuring and verifying a specified eligibility criterion call for effective targeting methods to identify the population of interest. A variety of methods exist for this purpose. Two of the most common targeting methods in Sub-Saharan Africa are PMT and HEA.

### 2.1 PMT: Description and literature

PMT generates a proxy for household welfare—normally measured by household expenditures—that determines program eligibility through household and individual characteristics that are easy-to-verify and measure (Grosh and Baker 1995). Characteristics often include a household’s location and quality of dwelling, the ownership of durable goods, demographic structure, education, and occupations of adult members. The selection and weights of characteristics are determined through statistical models that predict household welfare using comprehensive household surveys.

PMT is normally combined with other targeting methods including geographical targeting and/or community based targeting (CBT). The main advantage of PMT is that it provides fairly good targeting results for chronically poor households using a comparatively small amount

of information that is easy to observe and relatively hard to manipulate. In addition, the PMT does not discourage work or distort other incentives for households to increase their levels of well-being, because applicants do not know which variables, and their respective weights, determine the welfare/poverty level. However, PMTs do not normally perform well in targeting households vulnerable to poverty. In other words, while a PMT can provide an accurate picture of the poverty level at the time of data collection, it does not take into account the likelihood of shocks and how these may affect households.

There is an important amount of evidence on the effectiveness of PMT. Del Ninno and Mills (2014) conclude that it is possible to effectively target chronically poor households using PMTs based on multi-country case studies from Sub-Saharan Africa. However, PMT efficacy remains an open issue with respect to the identification of beneficiaries vulnerable to poverty. Also, the authors suggest that further improvements are possible in the design of PMT tools to substantially improve targeting performance by combining PMTs with other targeting methods.

Using data collected in a pilot cash transfer program in Niger, McBride (2015) evaluates the performance of the PMT assessed in this paper on the basis of different food security indicators. The study shows mixed results. For some food insecurity indicators such as the coping strategy index the study found a relatively weak but significant correlation with the PMT. For other indicators such as the Food Consumption Score, it found no significant correlation.

A large experiment in Indonesia compared the effectiveness and acceptability of PMT, CBT, and a hybrid method combining the two (Alatas et al. 2012). Atlas et al. find that PMT is only marginally more efficient than the other methods while CBT results in better community acceptability. In Cameroon, a study by Stoeffler, Mills and Del Ninno (2016) reports a slightly better performance of PMT targeting in identifying households with low per capita consumption than the CBT. However, community choice seems to be driven by different factors associated with poverty such as income potential, which includes human and physical

capital. Karlan and Thuysbaert (2013) use data from Honduras and Peru to examine the effectiveness of a hybrid two-step process that combines a participatory wealth ranking and a verification household survey, relative to two proxy means tests. All methods performed similarly on the basis of various metrics. Given similarities in effectiveness the authors suggest that the decision should be driven by costs considerations.

## 2.2 HEA: Description and literature

The Household Economy Approach (HEA) is based on a livelihoods analysis framework for analyzing household livelihoods and understanding how different shocks may affect them.<sup>3</sup> A key feature of the approach is the production of an “HEA baseline”, which comprises three main steps. The first step, the livelihood zoning, defines livelihood zones, i.e. geographical areas within which people share broadly the same patterns of access to food and income and have the same access to markets. The second step, the wealth breakdown, groups the population within each livelihood zone into different wealth categories. It then provides the household characteristics and quantifies the assets within each wealth group. The third step, the livelihood strategy step, provides a quantified estimate of food and income needs for households in each wealth group.

The HEA was developed by Save the Children UK and the Food Economy Group (FEG) in the 1990s in order to improve the ability of humanitarian agencies to anticipate and respond to shocks affecting food access (Holzmann et al. 2008). Since then, the method has been further developed and adapted for different purposes, among them household-level social protection targeting, which is the focus of this paper. Today, humanitarian agencies rely on “household level HEA targeting” as one of the most commonly used methods in identifying households during crises for their vast programs in the Sahel. In 2014 alone ECHO funding amounted to 202 million euros in response to food crises reaching an estimated 1.7 million food insecure people (ECHO 2015). A large share of this population was reached through HEA targeting.

---

<sup>3</sup> For more details on the HEA, see Holzmann et al. (2008)

Normally, targeting criteria vary by livelihood zone and largely rely on the conducted HEA baseline. Yet, the exact way in which household level HEA targeting is implemented can vary depending on the implementing organization and country. For example, in Burkina Faso, Chad and Mali, HEA is implemented using a CBT approach together with the HEA baseline, but the extent to which the HEA baseline is used in guiding the CBT varies by country. In Niger, by contrast, HEA uses a formula in addition to CBT. Despite its importance and abundant use, up to this date there is limited quantitative evidence on the effectiveness of HEA as a targeting tool.

### 2.3 PMT and HEA methods used in Niger

The PMT formula evaluated in this paper was developed for the first phase of the World Bank funded social safety nets (SSN) project which targeted 40,000 households. The SSN project provided eligible households monthly cash transfers amounting 10,000 CFA and accompanying measures for 24 months. The targeted population were chronically poor households. To identify the population of interest, geographical and household level targeting approaches were used. The geographical targeting approach selected communes and determined beneficiary quotas in each through a poverty mapping exercise. Next, within each commune, beneficiary villages were randomly selected. The number of villages selected in each commune was set so that on average beneficiaries would represent 30 percent of the total population of households in a given commune. The household level targeting approach involved two main steps. First, a PMT method was applied to identify the 30 percent poorest households in the selected communes. While the PMT ranking within a commune ultimately determined the share of beneficiaries in each village, the minimum share of beneficiaries possible was set at 10 percent and the maximum at 80 percent. Second, a community validation process was applied.

The formula used for the PMT method evaluated in this study was calibrated using the EBCM 2007 national survey and had the explicit objective to proxy the consumption per capita of households. Variables used in the formula included household demographics, the ownership of goods, livestock, land, and dwelling characteristics.

The HEA household-level targeting method evaluated in this paper<sup>4</sup> was developed and used by the Alliance ECHO<sup>5</sup> in Niger to provide temporary cash transfers (for three to four months) aimed at supporting food insecure households during the lean season. While the PMT in Niger had the explicit objective of identifying households with low consumption per capita, the HEA household-level targeting method does not explicitly define a measurable benchmark. For instance, current users of the method in Niger have the objective to “improve the food and nutritional situation of the most *vulnerable households* during the lean season in Niger”.<sup>6</sup> Yet, there is no specific measurable definition of *vulnerable households*. As the SSN project implemented by the government, the Alliance also first relies on geographical targeting to select those areas most affected by shocks. Next, a household level targeting approach is conducted by following *two parallel processes*, in which roughly 30 percent of households are identified as beneficiaries in each village:

1. Two targeting committees (normally one composed of women and the other one of men) of about eight members each are formed. Using an exhaustive list of all households in the communities, each committee separately classifies each household into one of the four wealth groups.
2. A short survey is applied to every household in the community. Next, a formula is used based on the collected data to classify households into the four wealth groups. This formula was developed by the Alliance in 2014 based on historic targeting data in order to develop consistent criteria along which to categorize and select households. The formula relied on household demographics, livestock, land, the duration of food coverage using own agricultural production and monthly household revenues.

Once the three rankings, i.e. those from the two committees and that from the formula, are ready, any discrepancies are addressed by the NGOs together with community members before agreeing on a final classification of households. All households that are classified as

---

<sup>4</sup> Described in Bourahla et al, (2014).

<sup>5</sup> Alliance ECHO is a partnership of five different NGOs (ACF, Acted, Concern, Oxfam and Save the Children).

<sup>6</sup> (Bourahla et al. 2014).

“very poor” are then selected as beneficiaries. On average, 30 percent of households were classified as very poor.

This paper analyzes the performance of household level targeting only (and not the geographical level targeting). In particular, the present study evaluates the relative efficiency of the PMT and HEA formulas in areas that are representative of rural agro-pastoral zones. While both approaches use a community based approach to validate beneficiary lists obtained by applying each formula, the formulas are expected to closely match the final beneficiary lists. In fact, for the case of the PMT, the final beneficiary list obtained from the community validation process almost entirely overlaps with that obtained from the formula. Similarly, for the case of the HEA, the community based process (that involves the two targeting committees) closely matches the formula: around 90 percent of households identified as beneficiaries are also selected according to the formula (Bourahla et al. 2014). The fact that the community validation process closely overlaps with the PMT and HEA methods does not necessarily mean that communities’ poverty perceptions are the same as those from the PMT and HEA. Qualitative evidence suggests that during the validation process communities tend to retract from disagreeing with the provided list of beneficiaries because of cultural norms.

### 3. Data

The present paper relies on the 2011 National Survey on Household Living Conditions and Agriculture (ECVM/A). The ECVM/A is an integrated multi-topic household survey conducted to quantify poverty and living conditions in Niger. The ECVM/A involved two visits to the same households. Some survey modules were applied during both visits while others were applied during the first or second visit only. The first visit took place during the lean or “hungry” season, i.e. between June and August 2011. The second visit took place during the harvest season, i.e. between October and December 2011.

The household questionnaire used during the second visit is a reduced version of that used in the first round, except for the section on livestock which is only asked during the second

visit. The second visit questionnaire includes information to determine if members who were in the household in the first visit are still in the household and if there are any new members. When there are new members, the questionnaire is used to collect basic information on their socio-demographic. In addition, information for all households is collected again on non-food and food expenditures and food security.

The survey collected data from a total of 25,116 individuals from 3,968 households in 270 enumeration areas. The sample is nationally representative as well as representative of Niamey, urban areas (excluding Niamey) and rural areas. Within the rural enumeration areas, the sample is also representative of three ecological zones: agricultural, agro-pastoral, and pastoral. The present study restricts the sample to agro-pastoral zones only. This is because the HEA targeting formula was developed exclusively for agro-pastoral zones. The study makes use of survey household sampling weights throughout to maintain representativeness.

## 4. Methodology

### 4.1 Simulating PMT and HEA selection of beneficiaries

To evaluate the existing PMT and HEA methods, the present paper mimics the selection procedure based on the formula of each targeting method using the ECVM/A-2011 survey. Specifically, the application of each formula using the ECVM/A data provides both a PMT and HEA score for each household representing their predicted level of wellbeing. These scores are used to rank all households from worst off (those with the lowest scores) to best off (those with the highest scores) and considers those ranked below the 30th percentile of the respective distribution as beneficiaries. While the 30th percentile is chosen to approximate the share of beneficiaries actually selected by both methods, the study also analyzes how the performance changes at different cut-off points.

Applying the PMT approach based on the ECVM/A survey is straightforward since the ECVM/A contains nearly all<sup>7</sup> PMT variables needed to identify beneficiary households. The

---

<sup>7</sup> With the exception of having a handicap member in the household. Handicap status is thus excluded from the PMT formula that is simulated in this paper.

wording of the various questions is identical across both survey instruments. As a result, the PMT formula together with a cut-off point can be applied directly on the ECVM/A dataset to identify households that would be selected under PMT.

Identifying HEA households using the ECVM/A dataset is more complex given some differences in the way questions are asked between the ECVM/A and the HEA survey instruments. Specifically, while the HEA questionnaire tends to obtain information about some variables through a small number of questions, the ECVM/A survey relies on a much larger number of detailed questions. For instance, for variables including period of coverage by own agricultural production (in months) and income, the HEA questionnaire asks two questions, one for each variable while the ECVM/A survey has detailed modules on agricultural production and income. The HEA questionnaire also uses a limited number of questions about cultivated land, household size, number of children and ownership of livestock, while the ECVM/A survey uses a larger set of questions on the household roster, livestock ownership and land usage. Marital status and gender of the household head are asked in similar ways in both survey questionnaires. Table 1 (Annex 1) lists the targeting criteria used by HEA, and describes how these variables are constructed using the ECVM/A dataset.

The present simulation “constructs” HEA variables by relying on the detailed ECVM/A modules whereas the actual HEA method relies on a short survey. As such, the present study evaluates the PMT and HEA formulas, as opposed to the actual processes through which these formulas are implemented. Since this simulation relies on detailed modules to construct HEA variables, in reality the HEA method is likely to perform worse than simulation results. Not only some variables are difficult to collect through single questions (e.g. income and period of coverage by own agricultural production), but, given difficulties in verifying this information, household may have an incentive to under-report, especially in the context of a welfare program.

Another aspect to keep in mind in the simulation of methods relates to the timing of data collection. As mentioned the ECVM/A was implemented during both the lean and harvest season. While only those questions related to the household's composition and consumption were asked in both rounds, all other questions were asked in only one round. In constructing the necessary PMT and HEA variables the present study relies on the information from the first or second round only (for variables that were captured in only one round), or on the average of the two (for variables that were captured in both rounds). See Table 1, annex 1 for details on how each variable was constructed. The lack of some variables in one of the two rounds prevents an assessment of the impact of the timing of data collection. However, most variables used in both the PMT and HEA are not expected to change much (if at all) throughout a given year.

#### 4.2 Welfare benchmarks, vulnerability and targeting errors - concepts and definitions

##### *Welfare benchmarks*

To assess the efficiency of each method this paper analyzes targeting errors based on different observed welfare benchmarks. This paper primarily focuses on two welfare measures: consumption per capita as a measure of poverty, and the Food Consumption Score as a measure of food insecurity. As such, the paper uses the term “poor” to refer to households that have low levels of consumption per capita, and the term “food insecure” to those with a low FCS. In addition to these two welfare measures the study also evaluates the efficiency of targeting based on alternative indicators including income per capita, non-productive assets, livestock, and the amount of cultivated land.

Consumption has been the most popular welfare indicator used for both research and policy purposes in developing countries (Chaudhuri & Ravallion 1994). Research has shown that this metric—generally used to determine the official poverty rates in developing countries—is a good indicator of chronic poverty, as well as a good proxy for other poverty dimensions.

The consumption per capita measure was collected in both rounds of the survey. The present study explores the efficiency of targeting based on the consumption per capita for each round

separately, as well as the average consumption across the two rounds (which is the measure that was used to estimate the official poverty rate in Niger). The measure includes consumption expenditures coming from the following items: (a) food expenditures (including meals eaten outside the home); (b) non-monetary food consumption resulting from consumption of home production, gifts and in-kind payments; and (c) the purchase price of new non-durable goods and services, an imputed value of rent for dwellings owned by the household or rented free of charge by a third party, and an estimation of the use value of durable goods. The aggregate is built in three steps. First, all consumption expenditures are aggregated at the household level. Second, the aggregated consumption expenditures are divided by the household size to adjust for differences in household composition. Lastly, the measure is divided by a special deflator to take into account differences in the costs of living across different geographical areas in the country (INS 2013).

In addition to consumption per capita, this study explores the targeting efficiency based on consumption per adult equivalent as well as consumption per capita adjusted for economies of scales. These variations to consumption per capita are explained in more detail in section 7.2.

The FCS is a widely used food insecurity measure developed by the World Food Program (WFP) to proxy for household food security based on a seven-day food consumption recall (WFP 2008).<sup>8</sup> The FCS score takes into account not only the frequency of consumption of food items from 9 categories over the past seven days but also the quality – “nutrient density” – of the consumed food items which is constructed based on assigning weights to the nine food categories.

To look at the targeting efficiency based on livestock and non-productive assets, indices were constructed using principal components analysis (PCA). PCA is a statistical technique often

---

<sup>8</sup> Specifically, the module used to construct the FCS indicator asked the number of days during the last 7 days in which the household consumed each of the following products. Food groups included cereals and cereal products, tubers and plantains, legumes and seeds, vegetables, fish and meat, fruits, milk and milk products, oil and grease, sugar products, spices and condiments.

used in the creation of socio-economic status indices from household survey data. To create the livestock index, variables indicating the ownership of different types of livestock were used. To create the non-productive asset index the following set of variables were entered into the PCA: dwelling characteristics and ownership of household goods such as telephone, beds, chairs, furniture, etc. For each index, from a set of correlated variables, PCA creates uncorrelated components that explain the variance in the data and thus provide synthesized information on the underlying concept—in this case livestock and non-productive assets. The components are ordered so that the first component explains the largest amount of variation in the data. This first principal component is then used as an index (Vyas and Kumaranayake 2006; Filmer and Pritchett 2001).

### *Vulnerability*

Regardless of the benchmark, welfare is not static. Some households live in a state of constant deprivation, while others are exposed to deprivation only temporarily after experiencing a shock (Del Ninno and Mills 2015; Hodinott, Rosegrant, and Torero 2012; Tesliuc et al. 2014). A common definition of vulnerability is the probability (or risk) *today* of being in poverty or falling into deeper poverty in the future (Coudouel et al. 2002).

Measuring vulnerability to poverty remains challenging. Anticipated income or consumption changes matter to individuals and households *before* they occur—regardless of whether they actually occur at all—and *after* they have occurred. The probability of falling into poverty tomorrow is impossible to measure. Instead, one can analyze the dynamics and variability of consumption (or other poverty proxies) to gauge vulnerability. This requires panel data which is often unavailable or of poor quality in low income settings.

To address the non-static nature of welfare measures the present study relies on the two survey rounds within the same year. Particularly, it explores the extent to which each of the methods can identify households suffering from permanent or seasonal deprivations, defined as being deprived in both or one round only respectively.

### *Targeting errors*

Once benchmarks have been defined, inclusion and exclusion errors measure a targeting mechanism's effectiveness to identify the target population. The literature has used different definitions of inclusion and exclusion errors. The present study refers to inclusion error when households that are not "eligible" are selected by the targeting criteria and enrolled in the program. "Eligible" here is defined as households that are within 30 percent lowest scoring households based on a given metric. For instance, households are ranked according to different metrics. Next, the share of beneficiary households that are not within the 30 percent lowest scoring households for a given metric is calculated. By contrast, exclusion errors occur when "eligible" households are not selected by the targeting criteria and excluded from the program.

In other words, the study relies on the predicted welfare (derived from the PMT and HEA formulas) to replicate eligibility to the program, and then compares eligibility to the actual welfare observed in the same data to calculate the targeting errors.

This study sets the share of beneficiaries at 30 percent, which is equivalent to the share of "eligible" households. In this case the exclusion and inclusion error become the same, by construction. As such, in this paper we only talk about inclusion errors.

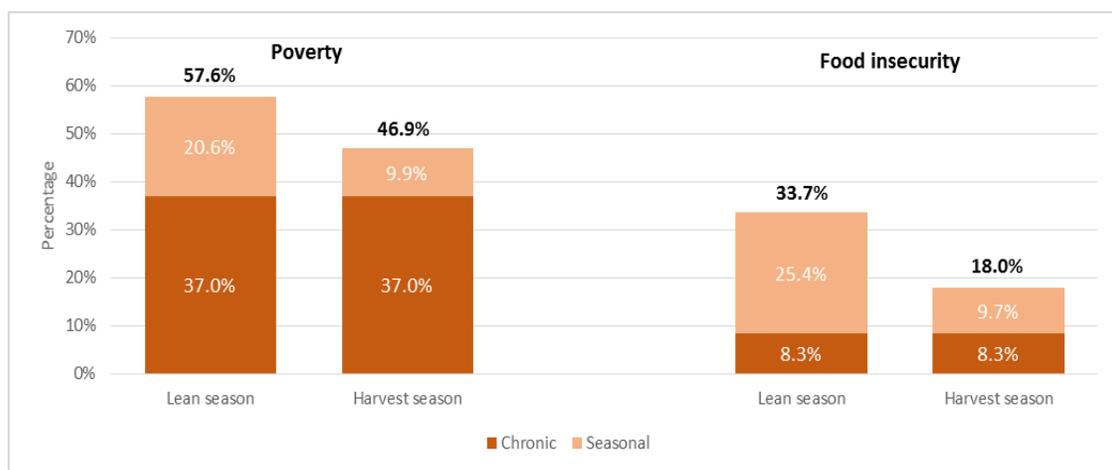
Inclusion errors result from both an imperfect targeting method and failures in implementing the targeting method. Because the present study conducts a simulation of formulas, it only captures the former. Inclusion errors from each method are compared to those from a random selection method to better illustrate the gains from each tool in identifying targeted populations.

## **5. Descriptive statistics on consumption per capita and the FCS**

This section provides key descriptive statistics of the main welfare measures used to assess targeting effectiveness, namely consumption per capita and the FCS. The height of bars in Figure 1 represents the total prevalence of poverty (measured using consumption per capita

and the national poverty line), and food insecurity (measured through the FCS and the food insecurity threshold), during the lean and harvest season.<sup>9</sup> The darker areas represent households suffering from “chronic” poverty or food insecurity. Chronic in this paper is defined as households that are below the poverty line/food insecure threshold in both survey sounds. The lighter areas represent households suffering from “seasonal” poverty or food insecurity. Seasonal in this paper is defined as households that are below the poverty line/food insecure threshold during one season only.

*Figure 1: Chronic and Transitory Poverty and Food Insecurity*



*Note:* Chronic poverty/food security is defined as being below the poverty line/food insecure threshold in both 2011 survey sounds (e.g. harvest and lean season). Seasonal poverty/food security is defined as being below the poverty line/food insecure threshold during one season only. Figure based on Table A1 and Table A2, Annex 2.

During the lean season, 58 percent of households were poor and 34 percent households were food insecure. The majority of poor households suffer from chronic poverty within the same year—among 58 percent of poor households during the lean season, 21 percent of them become non-poor during the harvest season. In contrast, food insecurity is mostly experienced transitorily, with the majority of households that are food insecure during the lean season becoming food secure during the harvest season (25 percent out of 34 percent).

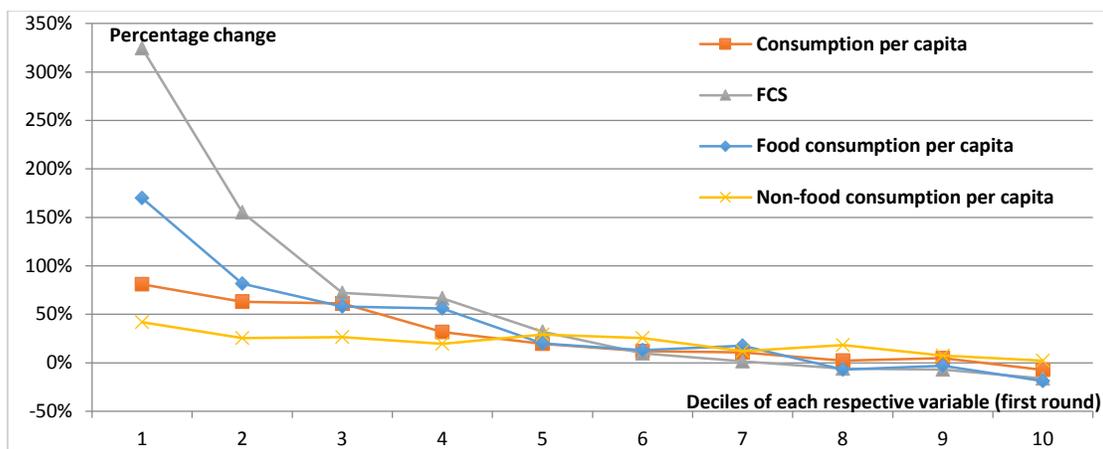
<sup>9</sup> A household is considered poor if his annual consumption per capita is below 182,635 FCFA. A household is considered food insecure if his FCS is less than 35 (INS Niger and World Bank 2013).

<sup>10</sup> Sectors include Agriculture & Fishing Wage Employment, Crop - Own Cons from Production Section, Livestock Production, Non-Ag Self Employment, Non-Ag Wage Employment, Private transfers.

In other words, about one in four households in Niger were seasonal food insecure while only 8 percent were chronically food insecure during the lean season in 2011. Lastly, during the harvest season there is a small share of households (around 10 percent) that experience transitory poverty and food insecurity. This result may be linked to idiosyncratic shocks, or covariate shocks that are not associated with the season.

While large seasonal variations exist in household welfare, these variations are not equally experienced across the welfare distribution. As shown in Figure 2, households in the bottom third of the distribution (of each respective variable) experience substantial variations in welfare between seasons. For instance, the consumption per capita of the poorest decile almost doubles in the harvest season. Most of this variation comes from the food part of consumption, where the percentage change is about 170 percent for the lowest decile, as opposed to the non-food part of consumption which changes by almost 50 percent. Yet, while the food consumption changes substantially, the FCS changes even more; for the poorest decile, the percentage change in the FCS is over 300 percent.

*Figure 2: Percentage Change in Welfare Measures between the Lean and Harvest Season*

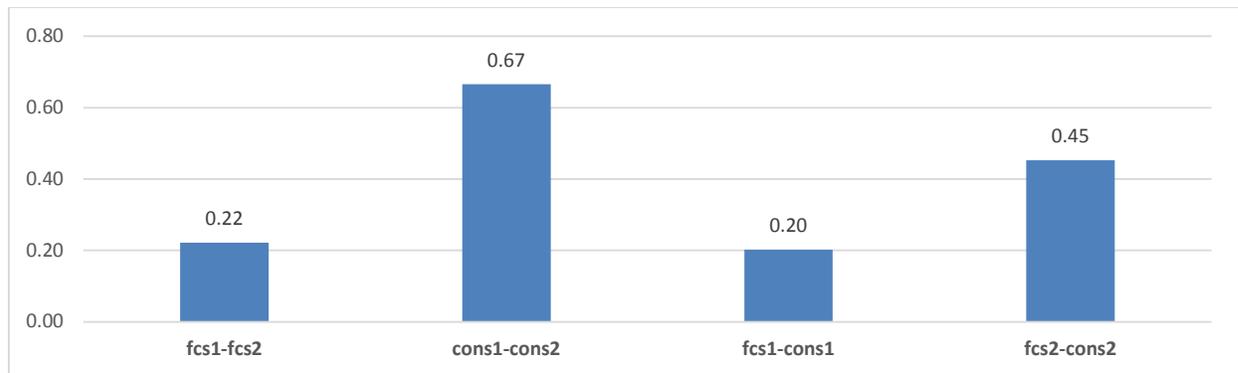


*Note:* for each different welfare measure, the figure presents the percentage change between the lean and harvest season for each decile relative to the first round. Graph is based on Table A3, annex 2.

Consistent with Figure 2, Figure 3 shows that consumption per capita is a more stable measure than the FCS; the correlation between consumption per capita in the first and second round is 67 percent versus only 22 percent for the FCS. The correlation between the

FCS and consumption per capita during the lean season is especially weak (20 percent). Nonetheless, during the harvest season, this correlation substantially increases to 45 percent. In sum, consumption and the FCS capture different components of household deprivation. Whereas the former tends to be more chronic in nature, the latter tends to be more seasonal.

*Figure 3: Correlations between Welfare Measures*



*Note:* The Figure shows correlation coefficients between different indicators: Fcs1/fcs2 and cons1/cons2 correspond to the FCS and consumption per capita respectively during rounds 1 and 2, i.e. the lean and harvest season. Figure is based on Table A4, annex 2.

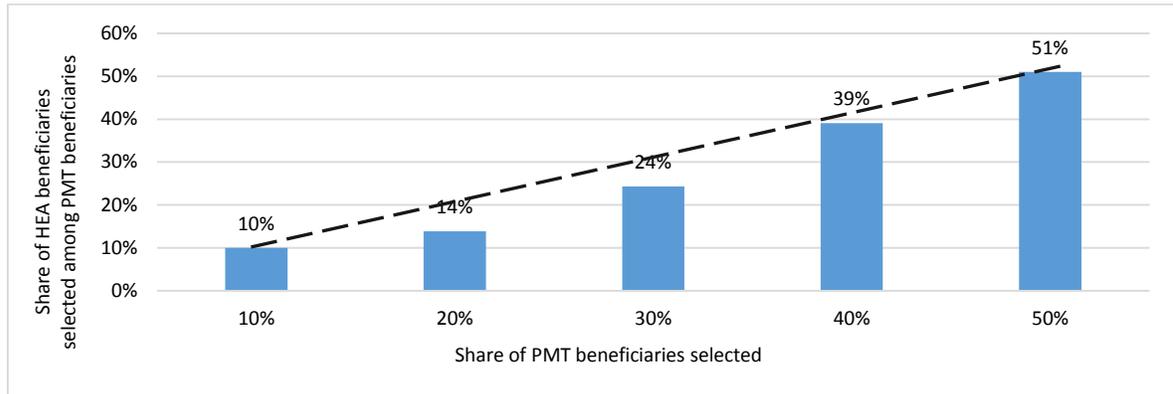
## 6. Households targeted under the PMT and HEA methods

### 6.1 Overlap between HEA and PMT

This section discusses the overlap of the existing PMT and HEA methods in Niger based on simulations performed. Figure 4 shows the overlap between beneficiaries selected by the PMT and HEA for different targeted shares of beneficiaries. The straight line illustrates the overlap between beneficiaries selected under the two different methods selecting beneficiaries at random, and shows that, by construction, the higher the share of beneficiaries the higher the chance of having two methods with a larger overlap.

The overlap between households selected under the PMT and HEA is limited and increases as the share of selected beneficiaries increases. For example, when selecting 30 percent of beneficiaries based on the PMT, and 30 percent of beneficiaries selected based on the HEA, only 24 percent among the PMT beneficiaries would also be HEA beneficiaries.

Figure 4: Overlap between Beneficiaries at Different Cut-Off Points



Note: Bars presents the overlap between beneficiaries selected under PMT and HEA for different shares of beneficiaries selected. The diagonal line represents the overlap between beneficiaries selected under two different methods selecting beneficiaries at random. Figures based on Table A5 in annex 2.

## 6.2 Targeting efficiency

### Key welfare benchmarks

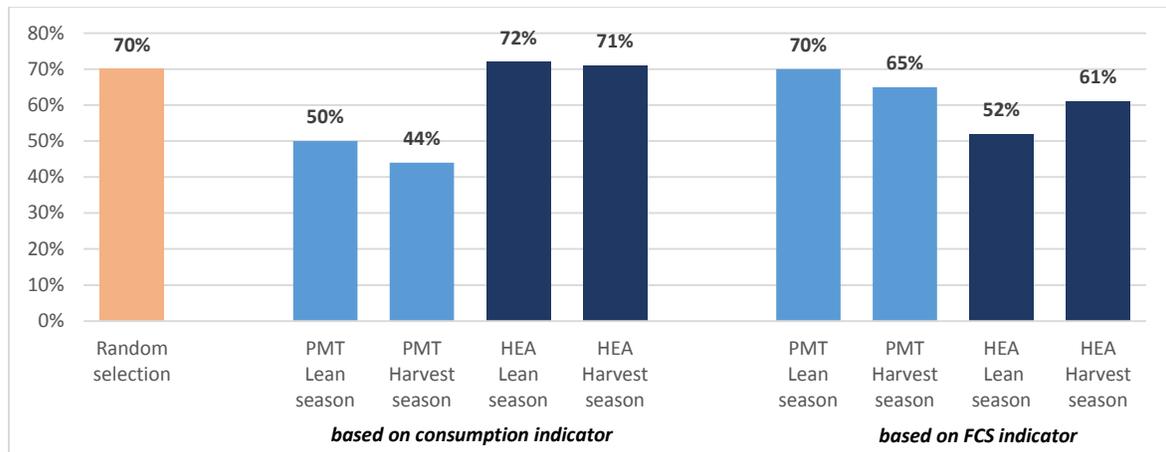
This section examines the targeting efficiency of PMT and HEA, starting with consumption per capita and the FCS as welfare benchmarks. The blue bars in Figure 5 show inclusion errors for the PMT and HEA on the basis of consumption per capita (denoted as “cons” in the graph) and the FCS during the lean (R1) and harvest (R2) season. The red bar denotes the inclusion error under a targeting tool that randomly selects households.

The performance of each method varies with the underlying indicator and the season. When relying on consumption per capita from the lean season as a benchmark, PMT clearly performs better. Specifically, when selecting the 30 percent of households with the lowest score of each respective method, the inclusion error is 50 percent for PMT versus 72 percent for HEA, a result that is no better than a random selection of households.

On the other hand, when using the FCS during the lean season as a benchmark the opposite is true; the inclusion error for PMT becomes 70 percent (no better than random selection) while this is 52 percent for HEA. In sum, during the lean season each method is best suited to

reach their designated objectives: the PMT better targets the poor (based on consumption per capita), whereas the HEA method better targets the food insecure (based on the FCS).

*Figure 5: Inclusion Error Based on Consumption and FCS - Selection of 30% of Households*



*Note:* bars present the inclusion errors during the lean season for different methods on the basis of different metrics. Inclusion errors are share of beneficiary households that are not within the eligible 30% lowest scoring households based on the metric used. A household is considered PMT or HEA beneficiary when it is within the 30% lowest scoring households based on the PMT and HEA score respectively. The red bar indicates the inclusion error under random selection. Figure is based on Table A6, annex 2.

The PMT method performs better in the harvest than in the lean season. This finding is likely driven by the fact that consumption is harder to predict during lean season; shocks (e.g. drought) are not observed, which translates into a higher error term during lean season.

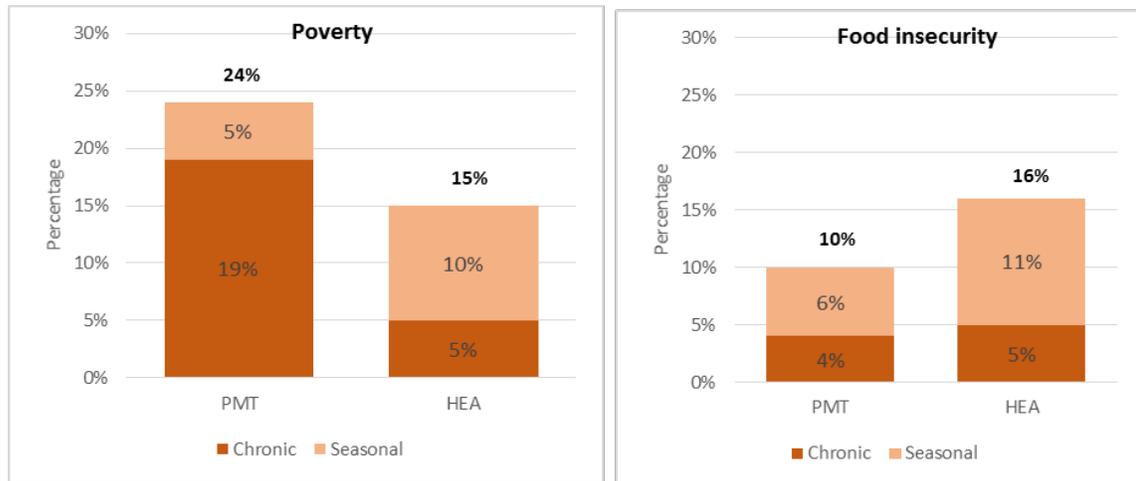
In contrast, the efficiency of HEA drops to 61 percent in the harvest season relative to 51 percent in the lean season. This is consistent with the nature of the underlying FCS welfare measure; the prevalence of food insecurity is much higher during lean than during harvest season (34 percent vs. 8 percent respectively).

Figure 6 shows the share of PMT and HEA selected households suffering from chronic (in darker color) and seasonal (in orange) poverty (left) and food insecurity (right), as a share of the population using the lean season as a base.

Overall, PMT is better at identifying households suffering from chronic poverty while HEA is better at identifying households suffering from seasonal food insecurity. PMT targets close

to twice as many households suffering from chronic poverty: PMT identifies 19 percent of households that are chronic poor, while HEA targets only 10 percent. When considering seasonal food insecurity, the opposite is true; HEA targets 11 percent of food insecure households while the PMT targets only 6 percent.

*Figure 6: Rates of Chronic and Seasonal Poor and Food Insecure among PMT and HEA Selected Households*



*Note:* Chronic poverty (food security) is defined as being below the poverty line (food insecure) threshold in both 2011 survey sounds (e.g. harvest and lean season). Seasonal food security is defined as being below the poverty line (food insecure threshold) during the lean season only. Figures based on Table A7 and Table A8, annex 2.

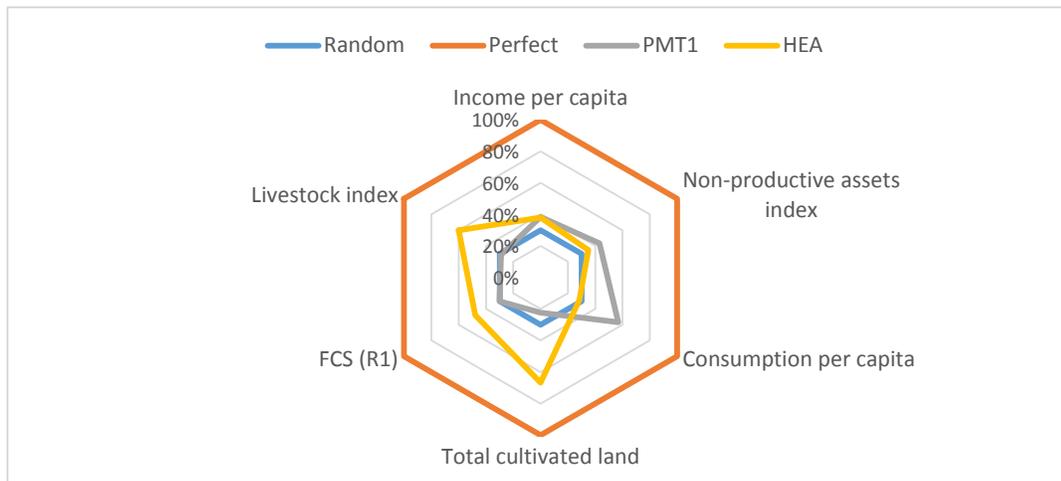
### *Alternative indicators*

This section explores the efficiency of methods based on alternative indicators. Figure 7 extends the PMT and HEA comparison by considering alternative indicators other than consumption and the FCS. Specifically, Figure 7 shows the share of households targeted under the two methods that are “deprived” in different dimensions (i.e. rank among the 30 percent lowest scoring households based on different metrics). The orange line represents outcomes under a perfect targeting method (as a theoretical benchmark) while the blue line represents outcomes under a method that randomly identifies beneficiaries. As such, the closer to the orange line and the further away from the blue line, the better the targeting performance. More details can be found in Table A9, annex 2.

As reflected in the figure, HEA can identify particularly well households with little agricultural related assets. For instance, 61 percent and 67 percent of households targeted by HEA are correctly targeted eligible households based on livestock and total cultivated land, respectively.

On the other hand PMT better identifies households with little non-productive assets; 43 percent of households selected by the PMT are correctly targeted eligible households on the basis of a non-productive index. In terms of income per capita, both methods perform similarly poorly. This is likely due to the difficulties in accurately measuring income in a context with high seasonality and a high consumption reliance on self-production.

*Figure 7: Share of Targeted Households That Are “Deprived” Based on Different Metrics*



*Note:* this figure compares the performance of PMT and HEA targeting to a perfect and a random targeting benchmark for six different metrics. Since both the PMT and HEA method identified roughly 30% of the population, a household is considered “deprived” according to each metric if it ranks among the 30% lowest scoring household on the metric. The orange line represents a scenario where households are perfectly identified under each metric, while the blue line corresponds to the performance of a method that randomly identifies households. Non-productive assets index included items such as dwelling characteristics and ownership of household goods such as telephone, beds, chairs and furniture. Figure based on Table A9, annex 2.

### 6.3 Characterizing households under each method

This section further describes differences between the two methods by looking at a variety of household characteristics. Despite having a much lower poverty rate, HEA households may appear to be “less resilient” on the basis of three main characteristics. First, the household

size of HEA households is considerably smaller than for PMT households (Table 1). In fact, PMT households have 9 household members on average versus only 5 members for HEA households. A larger number of household members might improve intra-household risk sharing and thus enhance households' ability to cope with a shock. Second, HEA households have considerably less livestock which can be an important coping mechanism for households to deal with shocks. Third, HEA households have less diversified livelihoods, with the average PMT household engaging in 2.5 different sectors while the average HEA household only works in 1.9 (Table A10).<sup>10</sup> Specifically, PMT households are more likely to participate in agriculture & fishing, wage employment, crops (own consumption), livestock production, and non-agricultural self-employment. Livelihood diversification is an important factor affecting resilience (Ellis 1998). When households have more diversified livelihoods they can rely on alternative sources of income when any given shock affects any particular type of livelihood.

There is also indication that HEA households may have more migrant members. About a fifth (21 percent) of the income of HEA households comes from remittances versus 9 percent for PMT households (Table A11). This may be part of the reason why HEA households may have higher consumption despite owning fewer productive assets. There is also the concern that providing social transfers to households already receiving private transfers may result in the crowding out of private transfers as opposed to increased household welfare (Albarran and Attanasio 2002).

Also, only 11 percent of PMT households have a female headed household versus 26 percent for HEA households. This could be an indication that—to some extent—there may be HEA households with male migrant former household members. Unfortunately the data does not contain information on migrant members so this hypothesis cannot be tested.

---

<sup>10</sup> Sectors include Agriculture & Fishing Wage Employment, Crop - Own Cons from Production Section, Livestock Production, Non-Ag Self Employment, Non-Ag Wage Employment, Private transfers.

Table 1: General Characteristics of PMT and HEA Households

	(1) PMT	(2) HEA	(1) – (2) PMT-HEA
Household size	9.1	4.8	4.31***
Dependency ratio (0-9 and above 60)	0.48	0.44	0.04**
Female headed household	0.11	0.26	-0.15***
Consumption per capita (R1&R2)	142,470	207,762	-65,292***
Poor (R1&R2)	0.82	0.47	0.35***
Energy consumption per capita R1	2,142	2,441	-299***
Energy consumption per capita R2	2,053	2,314	-261***
FCS R1	47	37	10***
FCS R2	55	54	1
Has land	0.99	0.89	0.11***
Number of plots	3.2	1.7	1.5***
Has radio	0.35	0.30	0.05
Has mobile phone	0.19	0.27	-0.08**
Has cart	0.21	0.05	0.16***
Has house/dala	1.00	0.89	0.10***
Number of small ruminants	2.9	1.1	1.9***
Poultry owned	3.7	1.2	2.4***
Polygamous family	0.39	0.07	0.33***
Number of large ruminants	0.5	0.0	0.50***
Duration of food production (month)	3.5	2.0	1.5***
Cultivated land (hectares)	17	5	12***
Age of household head	47	44	3**

Note: Statistical significance denoted \* = 10%, \*\* = 5%, \*\*\* = 1%. The p-values are based on t tests for the equality of means.

## 7. Can the design of formulas be improved?

### 7.1 Design of HEA

Two important challenges related to the implementation of the HEA method exist. The first challenge relates to the replicability of the HEA method used in Niger to other contexts or countries. As mentioned, the weights of the HEA formula were *qualitatively* assigned based on the NGO's field experience during several years. As such, the development of weights fully relied on context-specific experience that is not easily replicated.

The second challenge relates to the fact that variables used for the HEA method are not easy to measure and verify, which is likely to result in substantial measurement error. Relatedly, it is important to keep in mind that the present study relied on detailed modules on income and household production to construct the variables used in the HEA formula. In reality, the HEA method in Niger measures these variables through a considerably shorter questionnaire (normally with one question per indicator). As such, efficiency results presented in this paper are likely better than in reality. While a shorter questionnaire may considerably reduce costs of data collection, measurement errors are likely to be substantial given the complexity of these measures.

This section aims to see whether these challenges can be addressed by relying on a quantitative (rather than a qualitative) approach to determine the formula's weights, and by using variables that are easy to measure and verify. Such a quantitative approach would have the advantage of being (1) more easily replicated by exclusively relying on data and the choice of indicators, and (2) more efficient by minimizing measurement errors.

Two quantitative methods of determining the formula's weights are explored and juxtaposed. The first method follows the same methodology as the PMT, that is, a linear regression model that approximates a welfare measure. The welfare measure in this case is food insecurity during the lean season (as opposed to consumption per capita, which was used for the PMT). The regression model that best predicts the FCS is selected using a stepwise procedure. The second method is a Principal Component Analysis (PCA) approach, which synthesizes into one indicator all information contained from a set of variables (in this case, among variables used by the HEA).

Table 2 shows the inclusion errors of the different quantitative approaches; for comparability purposes, model 1 shows the inclusion errors for the existing HEA method. Model 2 shows the results of a linear regression model estimating FCS during the lean season and relying solely on variables that are relatively easy to measure and verify.<sup>11</sup> Model 3 also shows the

---

<sup>11</sup> Variables included household composition, dwelling characteristics, land, livestock and other assets

results of a linear regression model estimating FCS during the lean season, but this time including all variables used in HEA (such as period of coverage by own agricultural production and income) in order to quantify how much additional explanatory power these variables would add to the model. Finally, models 4-6 show results based on PCA that rely on livestock data only (model 4), livestock and assets (model 5), and livestock and land (model 6).

The two linear regression models that estimate the FCS (models 2 and 3) perform substantially better than the existing HEA method (1) at identifying households with a low FCS. Yet their performance is only slightly better for consumption per capita, and substantially worse for land and assets. Importantly, the inclusion of the additional variables that are not easy to measure and verify (model 3 vs. model 2) does not significantly lower the inclusion errors, which is why the more parsimonious model (model 2) is preferred.

The PCA approach relying on livestock only (model 4) nearly mimics the HEA method in terms of efficiency with the exception of two welfare measures, i.e. livestock for which the PCA targets perfectly (by construction) and land for which the PCA approach performs worse. Adding assets to the PCA approach (model 5), results in an improvement in terms of consumption and assets, but worsening of the FCS and livestock, relative to model 4. Finally, adding land (instead of assets) to the PCA (model 6), results in a slight improvement of efficiency based on land, but a slight worsening in terms of livestock, relative to model 4.

In sum, models 2 or 4 are preferred over models 3, 5 and 6 given the reduced number of variables it uses and its efficiency in terms of different welfare benchmarks. Results in this section showed that it is possible to achieve results largely similar to those from HEA through a quantitative model and without relying on variables that are hard to measure and verify.

*Table 2: Inclusion Errors of Quantitative Methods Aiming to Replicate HEA*

Welfare measure	(1) HEA	(2) LR - FCS	(3) LR - FCS add. variables	(4) PCA - Livestock	(5) PCA - Livestock & assets	(6) PCA - Livestock & land
Consumption pc R1	72%	71%	70%	72%	64%	72%
Consumption pc R2	71%	63%	63%	70%	64%	71%
Cons. pc avg. R1&R2	71%	66%	66%	73%	64%	74%
FCS R1	55%	42%	40%	54%	65%	54%
FCS R2	59%	59%	61%	59%	58%	59%
Land	33%	56%	54%	58%	62%	51%
Livestock	43%	43%	44%	0%	55%	8%
Asset	61%	70%	74%	62%	19%	63%
Income per capita	64%	60%	54%	67%	70%	68%

*Note:* Percentages represent the inclusion errors for different methods on the basis of different metrics. Inclusion errors are defined as the share of beneficiary households that are not within the 30% lowest scoring households based on the metric used. A household is considered beneficiary when it is within the 30% lowest scoring households based on the predicted score of each respective model.

## 7.2 Adjusting consumption for economies of scale and adult equivalent

As mentioned above, there is a large difference in average household size between households selected by the existing PMT versus those selected by the HEA method. A potential explanation for this discrepancy may be that the existing PMT method estimates consumption per capita without considering the household's composition and economies of scale. Specifically, households of different size and composition may have different needs or consumption costs, and not adjusting for these differences in needs can result in biases. There are two types of adjustments that can help address this problem – adjustments for (1) adult equivalence and (2) economies of scale. The former takes into account that a household member's consumption varies with age, and that e.g. young children do not consume as much as adults. The latter takes into account that larger households may be able to purchase goods in bulk, and hence consume at cheaper unit prices, especially for consumer durables.

Evidence from other studies have shown that communities also adjust for household composition and/or economies of scales in their targeting. For instance, a randomized targeting study in Indonesia comparing efficiency outcomes between PMT, CBT and a hybrid

method of the two found that the CBT method adjusts for economies of scale when selecting households (Alatas et al. 2012). Similarly, a study in Ghana finds that PMT and CBT methods systematically target groups of different household size (Pop 2015).

This section aims to test whether adjusting PMT models for economies of scale or household composition results in targeting outcomes closer to the HEA method (e.g. better performance in terms of FCS). To achieve this objective, two additional models are developed and tested, the former adjusting consumption per capita with an adult equivalence (AE) scale while the latter adjusts for consumption per capita for economies of scale (ES).

Table 3 shows the inclusion errors of the existing PMT formula (1), the new AE adjusted PMT formula (2) as well as the new ES-adjusted PMT formula (3). The analysis shows that adjusting for AE or ES does not result in a profile of beneficiaries that is more similar to the HEA method.

*Table 3: PMT Inclusion Errors When Adjusting for Household Composition*

Welfare measure	(1) PMT	(2) PMT-AE	(3) PMT-ES
Cons. pc R1	50%	45%	42%
Cons. pc R2	44%	43%	40%
Cons. pc avg. R1&R2	43%	39%	36%
FCS R1	70%	69%	68%
FCS R2	65%	62%	60%
Land	78%	78%	74%
Livestock	71%	78%	75%
Asset	57%	64%	59%
Income per capita	61%	65%	59%

*Note:* Percentages present the inclusion errors for different methods. These are shares of beneficiary households that are not within the 30% lowest scoring households based on each respective welfare measure. A household considered to be a beneficiary when it is within the 30% lowest scoring households based on the PMT score.

## 8. How can the existing methods be used in the context of ASP systems?

Based on the findings discussed in previous sections the present study proposes two main approaches in using these methods in the context of ASP; (1) a combination of the two targeting methods for programs to reach both, chronically poor households and those suffering from temporary food insecurity; (2) the harmonization of data collection tools by PMT and HEA users. Both of these ideas are discussed next.

### 8.1 Combining PMT and HEA to get the best out of each method

As previously mentioned, ASP systems aim to target both, chronically poor households and those affected by shocks. Given this objective, ASP could rely on a combined approach using the PMT to reach chronically poor households and HEA to reach households suffering from seasonal food insecurity.

This section simulates a system that would use the PMT to target 30 percent of households under a permanent program, and use the HEA to scale up the program in response to food insecurity crises by adding 10 percent of households as beneficiaries. This scenario assumes that households suffering from food insecurity during the lean season in our data only do so during the year in which the data was collected (i.e. the food insecurity is treated as a temporary shock). Preliminary analysis of two new survey rounds conducted during the lean and harvest season in 2014 on the same households sampled in the ECVI/A 2011 survey provides support to this assumption. Only 3 percent of households in agro-pastoral areas suffered from chronic food insecurity in both 2011 and 2014. Further, of those who suffered seasonal food insecurity in 2011, only 1 in 5 (20 percent) are also reported as seasonally food insecure in 2014. Because households experiencing food insecurity in 2011 and 2014 are not the same, the analysis suggests food insecurity may be experienced depending on temporary shocks.

Table 4 shows the efficiency (inclusion errors) of the PMT (1) and HEA (2) current programs and the expanded program during crises (3). Specifically, model 3 presents the inclusion error

for the 10% of households selected using HEA, after targeting 30 percent of households using PMT (1).

Results show that combining PMT with HEA can effectively identify households suffering from chronic poverty and temporary food insecurity. The efficiency of HEA greatly improves when selecting 10 percent (model 3) as opposed to 30 percent (model 2) of the population. For instance, the inclusion errors based on food insecurity during the lean season decrease from 52 to 38 percent. Inclusion errors based on land decrease from 33 percent to 7 and 8 percent. For livestock inclusion errors decrease from 40 percent to 28 and 29 percent. The large decreases in inclusion errors suggests that HEA can be an effective method to reach those at the very bottom part of the distribution on the basis of food insecurity and other metrics of well-being. Also, by covering a larger share of households in the same geographical areas (40 percent under the expanded program as opposed to 30 percent), the targeting costs per beneficiary is lower. This is because the fix cost of conducting a census in a given area can be spread across a larger number of beneficiaries.

*Table 4: Inclusion Errors for Current Programs and Scenarios 1 and 2.*

<i>Model</i>	<b>Current programs</b>		<b>Expanded program during crises</b>
	1	2	3
<i>Welfare measure</i>	PMT	HEA	HEA
<i>Share of households selected</i>	30%	30%	10% (after 30% PMT) = 40%
Cons. pc R1	50%	72%	83%
Cons. pc R2	44%	71%	82%
Cons. pc avg. R1&R2	43%	72%	84%
FCS R1	70%	52%	38%
FCS R2	65%	61%	63%
Land	78%	33%	8%
Livestock	71%	40%	29%
Asset	57%	65%	65%
Income per capita	61%	62%	62%

*Note:* Inclusion errors are defined as the share of beneficiary households that are not within the 30% lowest scoring households based on the metric used.

## 8.2 Harmonize data collection tools applied by PMT and HEA users

ASP systems aim to quickly respond to shocks. Yet a key constraint to quick and efficient shock-responses is the availability of unified registries that allow for both quick identification

of households in need and coordination among different actors providing aid. One main step in building such a unified registry is the creation, and use, of a common, harmonized data collection tool. While the PMT and HEA methods target significantly different populations, they both largely rely on the same type of information. The similarity in variables used implies that PMT and HEA data collection tools would only need trivial adjustments in order to be harmonized with each other. The harmonized questionnaire, therefore, could capture all beneficiaries' data needs so that the collected data has all the necessary variables to allow for different programs to target beneficiaries according to their own eligibility criteria. Furthermore, the harmonized questionnaire would improve efficiency of ASP systems through three main channels. First, it minimizes data collection costs since the same data can be used by different partners; all data is collected in the agreed format that is useful to all actors. Second, the harmonized tool would allow greater coordination amongst social protection actors and reduce overlap or unintentional double targeting of households. Third, it would allow for broader and quicker responses to shocks because programs can be scaled up based on the existing registry.

## 9. Conclusion and policy implications

The PMT and HEA are among the most widely used methods in Sub-Saharan Africa to target cash transfer beneficiaries. PMT is normally used to target chronically poor households and the HEA is used in the context of emergency programs to target food insecure households. This is the first study that provides quantitative evidence on the overlap and the relative performance of these methods by addressing four key questions:

1. What is the overlap between households selected under the PMT and HEA method?
2. What is the relative efficiency of the PMT and HEA based on key welfare benchmarks?
3. How can the methods be improved?
4. How can the existing methods be used in the context of ASP systems?

Results showed limited overlap between households selected under the PMT and HEA methods. PMT is more effective at identifying households suffering from chronic poverty

while the HEA is more effective at identifying household suffering from seasonal food insecurity.<sup>12</sup>

Households selected by the PMT tend to consume less calories per capita, are relatively larger, have less non-productive assets and more diversified livelihoods. Households identified by the HEA are characterized by a smaller household size, lower levels of livestock and land, and less diversified livelihoods. Those differences in characteristics may suggest that households identified through HEA may be less able to cope with shocks than households identified through the PMT. Households with a smaller size, lower levels of livestock and less diversified livelihoods may be less capable of sharing risk across household members, less likely to rely on livestock as a buffer, and less likely to have alternative sources of revenues when a shock affects a particular source of livelihood.

Importantly, this study evaluates the PMT and HEA formulas, and does not evaluate the process through which these are implemented. Given the simulation relies on detailed modules to construct HEA variables (as opposed to a limited set of questions as would be case for an actual HEA questionnaire), the HEA method is likely to perform worse in reality than the simulation results suggest. Not only are some variables difficult to collect through single questions but household may have in addition the incentive to under-report if variables are difficult to verify, especially in the context of a welfare program. Hence, several of the HEA variables collected through the HEA questionnaire are likely to include substantial measurement error which will ultimately have an impact on targeting efficiency. Based on the available data, this study cannot investigate the extent of these measurement errors. Future research could explore how these errors impact targeting efficiency.

A second challenge relates to the replicability of the HEA method used in Niger to other contexts or countries. The weights of the HEA formula were *qualitatively* assigned based on

---

<sup>12</sup> Chronic poverty is measured based on consumption per capita while food insecurity is measured based on the FCS during the lean season.

historical data from Niger, and as such may have limited value in contexts other than Niger if not adapted to a different context.

The study presented two strategies that can be used to address these two challenges, namely (1) choosing the formula's weights based on quantitative (rather than a qualitative) data, and (2) using variables that are easier to measure. Results showed that the HEA method can indeed be largely mirrored through a quantitative approach, like the PCA, which relies on easily measurable variables. Such a quantitative approach is more easily replicated since it is only based on data and the choice of indicators, and more efficient in minimizing measurement errors associated with difficult to measure variables.

Based on the above results the paper proposes two main approaches in using methods in the context of an ASP system; (1) a combination of targeting methods to reach both, chronically poor households and those suffering from temporary food insecurity; (2) the harmonization of data collection tools by PMT and HEA users.

Specifically, the study explored using the PMT to target 30 percent of households under a permanent program, which would then be expanded during food insecurity crises using the HEA for an additional 10 percent of households. This scenario assumes that households suffering from food insecurity during the lean season in our data only do so during the year in which the data was collected (i.e. the food insecurity is treated as a temporary shock). Preliminary analysis of two new survey rounds conducted during the lean and harvest season in 2014 *on the same households sampled in the ECVM/A 2011 survey* provides strong support to this assumption. Simulation results show that the efficiency of the HEA greatly improves when selecting the 10 percent additional households (after selecting 30 percent of households through the PMT). The more concentrated are the efforts in specific geographical areas with a higher percentage of coverage the lower the targeting cost per beneficiary.

Combinations of PMT with methods such as HEA, PCA, or a food insecurity formula may be considered to identify households suffering from chronic *and* seasonal food insecurity as part of an efficient and scalable ASP system. The application of these methods needs to be

accompanied by geographical targeting methods that can also identify both, areas suffering from chronic poverty (i.e. through as a poverty mapping exercise), and areas suffering from food insecurity (i.e. through the cadre harmonize). This is particularly relevant in Niger, where every year there are areas that are identified as food insecure.

Regardless of whether or not the PMT and HEA methods are used in combination, harmonizing data collection tools of PMT and HEA users would serve as a crucial building block towards a unified registry and play a key role in improving the efficiency of ASP systems. A unified registry would be used by multiple programs (for targeting, registration, and monitoring) and provide the basis for greater coordination, whilst also reducing overlap or unintentional double targeting. Each program could quickly identify households according to their objectives and criteria. Further, the similarity in variables used under both targeting methods implies that PMT and HEA data collection tools would only need slight adjustments to be harmonized with each other.

In sum, a first and essential step in choosing a targeting method is to clearly define the objective of the program and its corresponding welfare benchmark. If the program objective is to reach the chronically poor, a PMT formula that approximates consumption may be better suited. If the objective is to reach temporarily food insecure households, however, a HEA, linear regression model or PCA-based approach is likely to yield better results. Consistence in the selection of welfare measures is necessary, because, as illustrated in this paper, they are not always correlated with each other.

Finally, a prospective study in Niger testing the efficiency, acceptability and impact of three different targeting methods is currently being implemented. This prospective study will allow learning about the *actual* targeting efficiency of combining the PMT with other targeting approaches such as the HEA, PCA or a formula estimating food insecurity, on the basis of different welfare measures including consumption per capita and malnutrition.

## References

- 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* 102(4): 1206–40.
- Albarran, P., & Attanasio, O. P. 2002. "Do Public Transfers Crowd out Private Transfers? Evidence from a Randomized Experiment in Mexico (No. 2002/06)." WIDER Discussion Papers, World Institute for Development Economics (UNU-WIDER).
- Bourahla, L., Evrard-Diakite, M., Malam, A., Boulinaud, M. 2014. "Guide Méthodologique de Ciblage Basé sur la Méthode HEA," *Alliance Sécurité Alimentaire au Niger*.
- Chaudhuri, S., & Ravallion, M. 1994. "How well do static indicators identify the chronically poor?" *Journal of Public Economics*, 53(3): 367-394.
- Coudouel, A., Hentschel, J. S., & Wodon, Q. T. 2002. "Poverty Measurement and Analysis." *A Sourcebook for Poverty Reduction Strategies 1*: 27-74.
- Davies, M., Béné, C., Arnall, A., Tanner, T., Newsham, A., Coirolo, C. 2013. "Promoting Resilient Livelihoods through Adaptive Social Protection: Lessons from 124 Programmes in South Asia." *Development Policy Review* 31(1):27-58.
- Del Ninno, C., & Mills, B. (2015). Safety Nets in Africa: Effective Mechanisms to Reach the Poor and Most Vulnerable. *World Bank Publications*.
- ECHO Factsheet. 2015. "Sahel: Food & Nutrition Crisis", May.
- Ellis, F. 1998. "Household Strategies and Rural Livelihood Diversification." *The Journal of Development Studies* 35(1): 1-38.
- Hallegatte, S., Bangalore, M., Bonzanigo, L., Fay, M., Kane, T., Narloch, U. & Vogt-Schilb, A. 2015. *Shock Waves: Managing the impacts of climate change on Poverty*. Washington, DC: World Bank.

- Filmer, D., & Pritchett, L. H. 2001. "Estimating Wealth Effects without Expenditure Data—or Tears: An Application to Educational Enrollments in States of India\*." *Demography* 38(1): 115-132.
- Grosh, M., & Baker, J. L. 1995. "Proxy Means Tests For Targeting Social Programs," Working Paper, *Living Standards Measurement Study*, 118: 1-49.
- Haughton, J. H., & Khandker, S. R. 2009. *Handbook on Poverty and Inequality*. Washington, DC: World Bank.
- Hoddinott, John, Mark Rosegrant, and Maximo Torero. 2012. *Hunger and Malnutrition*. Copenhagen: Copenhagen Consensus Center.
- Holzmann, P., Boudreau, T., Holt, J., Lawrence, M. 2008. "The Household Economy Approach: a Guide for Programme Planners and Policy-Makers." Save the Children, London.
- Institut National de la Statistique du Niger (INS) and World Bank. 2013. "Profil et Déterminants de la Pauvreté au Niger en 2011 : Premiers Résultats de l'Enquête Nationale sur les Conditions de Vie des Ménages et l'Agriculture au Niger (ECVMA)".
- Karlan, D. and Thuysbaert, B. 2013. "Targeting Ultra-Poor Households in Honduras and Peru." NBER Working Paper 19646, November.
- McBride, L. 2015. "Evaluation of Targeting Methods and Impact of the Cash Transfer Pilot in Niger."
- McCord, A. 2012. "Community Based Targeting: A Review." Overseas Development Institute, London.
- Pop, L. B. 2015. "Options for Improving the Targeting of Safety Nets in Ghana." World Bank, Washington, DC.
- Stoeffler, Quentin, Bradford Mills, and Carlo del Ninno. 2016. "Reaching the Poor: Cash Transfer Program Targeting in Cameroon." *World Development*, Vol. 83.

- Tesliuc, Emil, Lucian Pop, Margaret Grosh, and Ruslan Yemtsov. 2014. *Income Support for the Poorest: A Review of the Experience in Eastern Europe and Central Asia*. Washington, DC: World Bank.
- Vyas, S., & Kumaranayake, L. 2006. "Constructing Socio-Economic Status Indices: How to Use Principal Components Analysis." *Health Policy and Planning* 21(6): 459-468.
- World Bank. 2014. *The State of Social Safety Nets 2014*. Washington, DC: World Bank.
- Wiesmann, D., Bassett, L., Benson, T., & Hoddinott, J. 2009. "Validation of the World Food Programmes Food Consumption Score and Alternative Indicators of Household Food Security." IFPRI Discussion Paper, International Food Policy Research Institute, Washington, DC.
- WFP (World Food Program). 2008. "Food Consumption Analysis: Calculation and Use of the Food Consumption Score in Food Security Analysis." Technical Guidance Sheet, WFP, Geneva.

## Annex 1: Comparability<sup>13</sup> of ECVM/A data with the HEA variables used for targeting

HEA variables	HEA survey instrument	ECVM/A survey instrument
Household size	It asks the respondent to report its “household size”. Normally NGOs use the following definition of household: <i>group of people living under the same roof and sharing the same pot of food.</i>	It asks the name of each household member and then adds up each member to get the total household size. The survey defines household as <i>a group of persons, related or otherwise, living habitually in the same dwelling, pooling their resources, sharing their meals, and recognizing the authority of the same person known as the household head.</i> This question is asked in both the first and the second visit. The average household size of the two rounds is used.
Marital status of household head	It asks the marital status of the household head. Household head is <i>defined by the household, commonly the male/husband of the family or a women when she is a widow or divorced.</i>	It asks for the marital status of the household head. Household head is defined as <i>the person who is accepted as such by the other household members. S/he generally exercises authority as the economic provider for the household.</i> This question is asked during the first visit.
The number of poultry owned by the household	It asks for the number of “poultry” owned by the household.	It asks separately how many chicken, guinea fowl, and « other birds » the household owns. The number of animals under these different categories are added up to construct the corresponding HEA variable. This information was only collected during the second visit only.
Number of small ruminants owned by the household	It asks for the number of “small ruminants” the household owns. This includes goats, sheep and donkeys.	It asks three different questions on the number of goats, sheep and donkeys owned by the household respectively. The number of animals from the three different questions are added up to construct the corresponding HEA variable. This information was only collected during the second visit.
Number of big ruminants owned by the household	It asks for the number of “big ruminants” the household owns. This includes cattle, camels and horses.	It asks three different questions on the number of cattle, camels and horses owned by the household respectively. The number of animals from the three different questions are added up to construct the corresponding HEA variable. This information was only collected during the second visit.

<sup>13</sup> HEA information used in the table is based on the HEA methodological guide developed by the alliance (Bourahla 2014). The way HEA questions are framed may slightly vary between different NGOs using HEA.

Land surface cultivated by household (in hectares)	It asks one question on the “the total land surface cultivated by household” (in hectares).	It asks for the area cultivated for each different crop. The area cultivated from each different crop is added to construct the corresponding HEA variable. This information was only collected during the first visit.
The duration of food coverage using own agricultural production (in months)	It asks one question on the duration of food coverage using own agricultural production (in months).	The instrument has a detailed food consumption module that asks for the consumption of different items during the past 7 days indicating whether the food consumed was bought or self-produced. In order to construct the corresponding HEA variable, two variables constructed from the consumption module are used in the following way: (food consumption resulting from consumption of home production / total food consumption)*12. Questions related to this indicator were asked in both the first and the second visit. The average of the indicator between the two rounds is used.
Average monthly household revenue	It asks one question on the average monthly household revenue (without specifying a timeframe). This is defined as money earned (in cash only) by household members.	The instrument has a detailed modules to capture different sources of income with different timeframes depending on the question. Income from the following three sources are added up in order to construct the HEA variable: (1) employment income for each household member; (2) income from household enterprises; (3) non-employment income. This information was only collected during the first visit.

## Annex 2: Tables<sup>14</sup>

*Table A1: Food insecurity by season*

<b>Food insecurity lean season (June-August)</b>		<b>Food insecurity harvest season (October-December)</b>		<b>Total</b>
		Food secure	Food insecure	
Food secure	#	501	97	598
	%	57%	10%	66%
Food insecure	#	201	68	269
	%	25%	8%	34%
Total	#	702	165	867
	%	82%	18%	100%

*Note:* Food insecure is defined as having a FCS that is lower than the food insecurity threshold.

*Table A2: Poverty by season*

<b>Poverty lean season (June-August)</b>		<b>Poverty harvest season (October-December)</b>		<b>Total</b>
		Non-poor	Poor	
Non-poor	#	289	89	378
	%	32%	10%	42%
Poor	#	168	321	489
	%	21%	37%	58%
Total	#	457	410	867
	%	53%	47%	100%

*Note:* Poor is defined as having a consumption per capita that is lower than the national poverty line.

<sup>14</sup> # indicates the number of observations and % indicates the population weighted shares.

Table A3: Percentage change in welfare measures between the lean and harvest season

Expenditure quintiles	Consumption per capita	FCS	Food consumption per capita	Non-food consumption per capita	Energy consumption per capita
1	0.81	3.24	1.70	0.42	1.23
2	0.63	1.55	0.82	0.26	0.43
3	0.61	0.72	0.58	0.26	0.18
4	0.32	0.66	0.56	0.19	0.11
5	0.20	0.32	0.20	0.29	-0.07
6	0.12	0.10	0.13	0.26	-0.16
7	0.11	0.02	0.18	0.12	-0.13
8	0.02	-0.06	-0.07	0.18	-0.13
9	0.05	-0.07	-0.03	0.07	-0.13
10	-0.07	-0.16	-0.19	0.02	-0.14

Table A4: Correlations between welfare measures

	fcs1	fcs2	pcexp1	pcexp2
fcs1	1			
fcs2	0.22	1		
pcexp1	0.20	0.17	1	
pcexp2	0.13	0.45	0.67	1

Table A5: Overlap between beneficiaries when selecting different shares of households

Share of PMT households selected	Beneficiary overlap with HEA	Beneficiary overlap with random method	#
10%	10%	10%	83
20%	14%	20%	162
30%	24%	30%	243
40%	39%	40%	329
50%	51%	50%	410

Table A6: PMT and HEA inclusion errors based on different welfare measures

Welfare measure	(1) Random selection	(2) Perfect targeting	(3) PMT	(4) HEA	(5) difference (3) - (4)	(6) difference (1) - (3)	(7) difference (1) - (4)
Cons. pc R1	70%	0%	50%	72%	-23%***	20%***	-2%
Cons. pc R2	70%	0%	44%	71%	-27%***	26%***	-1%
Cons. pc avg. R1&R2	70%	0%	43%	72%	-29%***	27%***	-2%
FCS R1	70%	0%	70%	52%	18%***	0%	18%***
FCS R2	70%	0%	65%	61%	4%	5%*	9%***
Land	70%	0%	78%	33%	44%***	-8%***	37%***
Livestock	70%	0%	71%	40%	31%***	-1%	30%***
Asset	70%	0%	57%	65%	-8%*	13%***	5%**
Income per capita	70%	0%	61%	62%	-1%	9%**	8%*

Note: Statistical significance of the test of differences in means is denoted as \* = 10%, \*\* = 5%, \*\*\* = 1 %

Table A7: PMT performance based on temporary and chronic poverty and food insecurity

		PMT		
		non-beneficiary	beneficiary	Total
Seasonal poor households	#	131	37	168
	% among all HHs	15.8	4.8	20.6
	% among seasonal poor HHs	76.9	23.1	100.0
Seasonal food ins. households	#	151	50	201
	% among all HHs	19.4	6.0	25.4
	% among seasonal food ins. HHs	76.3	23.8	100.0
Chronic poor HHs	#	161	160	321
	% among all HHs	17.7	19.3	37.0
	% among chronic poor HHs	47.8	52.2	100.0
Chronic food ins. HHs	#	42	26	68
	% among all HHs	4.7	3.6	8.3
	% among chronic food ins. HHs	57.2	42.8	100.0

Table A8: HEA performance based on temporary and chronic poverty and food insecurity

		HEA		
		non-beneficiary	beneficiary	Total
Seasonal poor households	#	122	46	168
	% among all HHs	15.1	5.4	20.6
	% among seasonal poor HHs	73.6	26.4	100.0
Seasonal food ins. households	#	115	86	201
	% among all HHs	14.0	11.4	25.4
	% among seasonal food ins. HHs	55.3	44.8	100.0
Chronic poor HHs	#	240	81	321
	% among all HHs	27.1	9.9	37.1
	% among chronic poor HHs	73.2	26.8	100.0
Chronic food ins. HHs	#	29	39	68
	% among all HHs	3.4	4.9	8.3
	% among chronic food ins. HHs	40.8	59.3	100.0

Table A9: Share of targeted households that are “deprived” based on different welfare measures

Welfare measures	(1) Random	(2) Perfect	(3) PMT	(4) HEA	(5) difference (1) - (3)	(6) Difference (1) - (4)
Income per capita	30%	100%	38%	38%	8% **	8% ***
Non-productive assets index	30%	100%	43%	35%	13% **	5%
Consumption per capita	30%	100%	57%	28%	27% ***	-2%
Total cultivated land	30%	100%	22%	67%	-8% ***	37% ***
FCS (R1)	30%	100%	30%	48%	0%	18% ***
Livestock index	30%	100%	29%	60%	-1%	30% ***

Note: This table shows “deprivation” rates among targeted households for each of the targeting methods (column) based on different welfare measures (rows). Since both the PMT and HEA method identified roughly 30% of the population, a household is considered “deprived” according to each welfare measure if it ranks among the 30% lowest scoring household on the welfare measure. Statistical significance of the ttest of differences in means is denoted as \* = 10%, \*\* = 5%, \*\*\* = 1 %

Table A10: Differences in livelihood diversification between PMT and HEA households

	PMT	HEA	PMT-HEA	p-value
Number of sectors in which the household is engaged	2.5	1.9	0.64	0.00
Participation rate:				
Participation - Agriculture & Fishing Wage Employment	0.12	0.05	0.07	0.00
Participation - Crop - Own Cons from Production Section	0.96	0.85	0.11	0.00
Participation - Livestock Production	0.75	0.48	0.27	0.00
Participation - Non-Ag Self Employment	0.64	0.45	0.19	0.00
Participation - Non-Ag Wage Employment	0.05	0.05	-0.00	0.86
Participation - Private Transfer	0.56	0.61	-0.05	0.22

*Table A11: Differences in livelihoods between PMT and HEA households*

	PMT	HEA	PMT-HEA
<b>Share of total income (share of means)</b>			
Share - Agriculture & Fishing Wage Employment	4.2	2.6	1.6
Share - Crop - Own Cons from Production Section	14.2	12.1	2.1
Share - Livestock Prod. - Food Section	24.1	14.0	10.1
Share - Non-Ag Self Emp	43.2	42.5	0.7
Share - Non-Ag Wage Employment	5.1	7.7	-2.6
Share - Private Transfer	9.2	21.1	-11.9

## **Social Protection & Labor Discussion Paper Series Titles 2014-2016**

<b><u>No.</u></b>	<b><u>Title</u></b>
1612	How to Target Households in Adaptive Social Protection Systems? Relative Efficiency of Proxy Means Test and Household Economy Analysis in Niger by Pascale Schnitzer, October 2016
1611	Pensions for Public-Sector Employees: Lessons from OECD Countries' Experience by Edward Whitehouse, October 2016
1610	Pension Systems in Sub-Saharan Africa: Brief Review of Design Parameters and Key Performance Indicators by Miglena Abels and Melis U. Guven, October 2016
1609	Household Enterprises in Fragile and Conflict-Affected States: Results from a Qualitative Toolkit Piloted in Liberia, Volume 2 – Annexes by Emily Weedon and Gwendolyn Heaner, August 2016
1608	Household Enterprises in Fragile and Conflict-Affected States: Results from a Qualitative Toolkit Piloted in Liberia, Volume 1 – Report by Emily Weedon and Gwendolyn Heaner, August 2016
1607	Benefits and Costs of Social Pensions in Sub-Saharan Africa by Melis U. Guven and Phillippe G. Leite, June 2016
1606	Assessing Benefit Portability for International Migrant Workers: A Review of the Germany-Turkey Bilateral Social Security Agreement by Robert Holzmann, Michael Fuchs, Seçil Paçacı Elitok and Pamela Dale, May 2016
1605	Do Bilateral Social Security Agreements Deliver on the Portability of Pensions and Health Care Benefits? A Summary Policy Paper on Four Migration Corridors Between EU and Non-EU Member States by Robert Holzmann, May 2016
1604	Assessing Benefit Portability for International Migrant Workers: A Review of the France-Morocco Bilateral Social Security Agreement by Robert Holzmann, Florence Legro and Pamela Dale, May 2016
1603	Assessing Benefit Portability for International Migrant Workers: A Review of the Belgium-Morocco Bilateral Social Security Agreement by Robert Holzmann, Jacques Wels and Pamela Dale, May 2016
1602	Assessing Benefit Portability for International Migrant Workers: A Review of the Austria-Turkey Bilateral Social Security Agreement by Robert Holzmann, Michael Fuchs, Seçil Paçacı Elitok and Pamela Dale, May 2016

- 1601 The Greek Pension Reform Strategy 2010-2016  
by Georgios Symeonidis, July 2016
- 1507 Integrating Disaster Response and Climate Resilience in Social Protection Programs in the Pacific Island Countries  
by Cecilia Costella and Oleksiy Ivaschenko, September 2015
- 1506 Effectiveness of Targeting Mechanisms Utilized in Social Protection Programs in Bolivia  
by Ignacio Apella and Gastón Blanco, September 2015
- 1505 Kyrgyz Republic: Social Sectors at a Glance  
by João Pedro Azevedo, Paula Calvo, Minh Nguyen and Josefina Posadas, August 2015
- 1504 Entering the City: Emerging Evidence and Practices with Safety Nets in Urban Areas  
by Ugo Gentilini, July 2015
- 1503 Pension Patterns in Sub-Saharan Africa  
by Mark Dorfman, July 2015
- 1502 Social Protection in Fragile and Conflict-Affected Countries: Trends and Challenges  
by Mirey Ovadiya, Adea Kryeziu, Syeda Masood and Eric Zapatero, April 2015
- 1501 Defining, Measuring, and Benchmarking Administrative Expenditures of Mandatory Social Security Programs  
by Oleksiy Sluchynsky, February 2015
- 1425 Old-Age Financial Protection in Malaysia: Challenges and Options  
by Robert Holzmann, November 2014
- 1424 Profiling the Unemployed: A Review of OECD Experiences and Implications for Emerging Economies  
by Artan Loxha and Matteo Morgandi, August 2014
- 1423 Any Guarantees? An Analysis of China's Rural Minimum Living Standard Guarantee Program  
by Jennifer Golan, Terry Sicular and Nithin Umapathi, August 2014
- 1422 World Bank Support for Social Safety Nets 2007-2013: A Review of Financing, Knowledge Services and Results  
by Colin Andrews, Adea Kryeziu and Dahye Seo, June 2014
- 1421 STEP Skills Measurement Surveys: Innovative Tools for Assessing Skills  
by Gaëlle Pierre, Maria Laura Sanchez Puerta, Alexandria Valerio and Tania Rajadel, July 2014
- 1420 Our Daily Bread: What is the Evidence on Comparing Cash versus Food Transfers?  
by Ugo Gentilini, July 2014
- 1419 Rwanda: Social Safety Net Assessment  
by Alex Kamurase, Emily Wylde, Stephen Hitimana and Anka Kitunzi, July 2012

- 1418 Niger: Food Security and Safety Nets  
by Jenny C. Aker, Carlo del Ninno, Paul A. Dorosh, Menno Mulder-Sibanda and Setareh Razmara,  
February 2009
- 1417 Benin: Les Filets Sociaux au Bénin Outil de Réduction de la Pauvreté  
par Andrea Borgarello et Damien Mededji, Mai 2011
- 1416 Madagascar Three Years into the Crisis: An Assessment of Vulnerability and Social Policies and  
Prospects for the Future  
by Philippe Auffret, May 2012
- 1415 Sudan Social Safety Net Assessment  
by Annika Kjellgren, Christina Jones-Pauly, Hadyiat El-Tayeb Alyn, Endashaw Tadesse and Andrea  
Vermehren, May 2014
- 1414 Tanzania Poverty, Growth, and Public Transfers: Options for a National Productive Safety Net  
Program  
by W. James Smith, September 2011
- 1413 Zambia: Using Social Safety Nets to Accelerate Poverty Reduction and Share Prosperity  
by Cornelia Tesliuc, W. James Smith and Musonda Rosemary Sunkutu, March 2013
- 1412 Mali Social Safety Nets  
by Cécile Cherrier, Carlo del Ninno and Setareh Razmara, January 2011
- 1411 Swaziland: Using Public Transfers to Reduce Extreme Poverty  
by Lorraine Blank, Emma Mistiaen and Jeanine Braithwaite, November 2012
- 1410 Togo: Towards a National Social Protection Policy and Strategy  
by Julie van Domelen, June 2012
- 1409 Lesotho: A Safety Net to End Extreme Poverty  
by W. James Smith, Emma Mistiaen, Melis Guven and Morabo Morojele, June 2013
- 1408 Mozambique Social Protection Assessment: Review of Social Assistance Programs and Social  
Protection Expenditures  
by Jose Silveiro Marques, October 2012
- 1407 Liberia: A Diagnostic of Social Protection  
by Andrea Borgarello, Laura Figazzolo and Emily Weedon, December 2011
- 1406 Sierra Leone Social Protection Assessment  
by José Silvério Marques, John Van Dyck, Suleiman Namara, Rita Costa and Sybil Bailor, June 2013
- 1405 Botswana Social Protection  
by Cornelia Tesliuc, José Silvério Marques, Lillian Mookodi, Jeanine Braithwaite, Siddarth Sharma  
and Dolly Ntseane, December 2013

- 1404 Cameroon Social Safety Nets  
by Carlo del Ninno and Kaleb Tamiru, June 2012
- 1403 Burkina Faso Social Safety Nets  
by Cécile Cherrier, Carlo del Ninno and Setareh Razmara, January 2011
- 1402 Social Insurance Reform in Jordan: Awareness and Perceptions of Employment Opportunities for Women  
by Stefanie Brodmann, Irene Jillson and Nahla Hassan, June 2014
- 1401 Social Assistance and Labor Market Programs in Latin America: Methodology and Key Findings from the Social Protection Database  
by Paula Cerutti, Anna Fruttero, Margaret Grosh, Silvana Kostenbaum, Maria Laura Oliveri, Claudia Rodriguez-Alas, Victoria Strokova, June 2014

**To view Social Protection & Labor Discussion papers published prior to 2013, please visit [www.worldbank.org/spl](http://www.worldbank.org/spl).**

## Abstract

Proxy Means Test (PMT) and the Household Economy Analysis (HEA) are widely used methods to target chronically poor households and those suffering from food crises respectively. Using panel data from Niger, this study provides the first empirical evidence on the relative efficiency of these methods in identifying households suffering from permanent or seasonal deprivations. Results show limited overlap between households selected by each method. The PMT performs better in targeting chronically poor households, while HEA performs better in targeting seasonal food insecure households. The study also explores the extent to which these methods can be improved, used and potentially combined to target households as part of ASP systems. Results show that the HEA formula could be further improved to target seasonally food insecure households, including through a regression model estimating food insecurity, and a principal component analysis (PCA) model. Combinations of PMT with methods such as HEA, PCA, or a food insecurity formula may be considered to identify households suffering from chronic poverty and seasonal food insecurity as part of an efficient and scalable ASP system. Harmonizing data collection tools of PMT and HEA users would serve as a crucial building block towards a unified registry and play a key role in improving the efficiency of ASP systems.

## About this series

Social Protection & Labor Discussion Papers are published to communicate the results of The World Bank's work to the development community with the least possible delay. This paper therefore has not been prepared in accordance with the procedures appropriate for formally edited texts.

The findings, interpretations, and conclusions expressed herein are those of the author(s), and do not necessarily reflect the views of the International Bank for Reconstruction and Development/The World Bank and its affiliated organizations, or those of the Executive Directors of The World Bank or the governments they represent. The World Bank does not guarantee the accuracy of the data included in this work. The boundaries, colors, denominations, and other information shown on any map in this work do not imply any judgement on the part of The World Bank concerning the legal status of any territory or the endorsement or acceptance of such boundaries.

For more information, please contact the Social Protection Advisory Service, The World Bank, 1818 H Street, N.W., Room G7-803, Washington, DC 20433 USA. Telephone: (202) 458-5267, Fax: (202) 614-0471, E-mail: [socialprotection@worldbank.org](mailto:socialprotection@worldbank.org) or visit us on-line at [www.worldbank.org/spl](http://www.worldbank.org/spl).