Targeting in Kenya's Cash Transfer Programme for OVC

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Abstract

This paper simulates the targeting performance of the Multidimensional Deprivation Index and Proxy Means Test approach using Kenya Integrated Household Budget Survey and the institutional setup of the Cash Transfer for Orphan and Vulnerable Children in Kenya. It reaffirms the earlier finding in the literature that there is no one preferred method or system when it comes to targeting eligible households. When we simulate the targeting performance of the MDI and PMT used previously and currently in the CT-OVC programme in Kenya, it seems that PMT consistently outperforms MDI with smaller inclusion error but under most circumstances has higher exclusion error. When the bottom 10% counting approach is used, PMT approach has a seemingly distinct advantage over MDI for both rural and urban samples. However, this apparent advantage of PMT turns out to be an artefact of the way we compare the PMT with MDI. We are comparing a PMT approach that has been customized to urban settings with a MDI approach without the necessary adjustment. Once the approaches are comparable, estimation results show that there is no discernable pattern on the relative advantage and disadvantage of them.

Key words: Cash Transfer; Orphan and Vulnerable Children; Targeting; Proxy Means Testing; Multidimensional Poverty

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Introduction

The Kenya cash transfer programme for vulnerable children was conceived during the run-up to the parliamentary elections at the end of 2002. Its conception stemmed from the realization that some elements of social protection in Kenyan society, especially family and communal mechanisms, were breaking down in the face of the growing AIDS pandemic. It was gradually accepted that this demographic momentum had led to increased numbers of orphans in Kenya as a consequence of AIDS.

By 2004, a first phase pilot programme was in place, targeting 500 households in three very different parts of the country (pastoralist areas, urban slums and a poor agricultural community), in a partnership between UNICEF (with partial funding from Sida) and the Government of Kenya (with funding from taxpayers). After two years of operation, the enthusiasm from the parliamentary committee and the Ministry of Home Affairs to relaunch the programme as a much larger pilot with design features that could be scaled up had grown to a tipping point. The second stage scaled up to 37 districts by 2008, with 75,000 households enrolled by the end of the 2008/09 financial year. In 2009, the World Bank agreed to an IDA loan worth US$50 million, running for five years from 2010 (Alviar and Pearson, 2009). During the fiscal year of 2009/10, the Programme expanded to reach approximately 75,000 households in 47 districts. Plans are currently under way to further increase coverage to 116,000 households by the end of June 2010. The financing of the programme has exploded with a ten-fold increased from 2004 to 2010.

As the programme expands, the need to target the right beneficiaries that most deserve the assistance escalates. It also becomes critical to the cost-effectiveness and efficiency as well as the credibility of the programme. The Kenyan government along with development partners involved in the CT-OVC programme has continuously explored ways to improve the targeting effectiveness since the inception of the programme. At inception, the targeting method was not clearly defined. During Phase 1 of the Pilot, members of the community were trained on a questionnaire to identify the most vulnerable children in each community. The questionnaires provided a list of eligible households (with poor OVC) in the selected areas. Given a pre-defined number of children to benefit from the intervention, three prioritization and selection processes were followed in each district. In Kwale District, after defining a maximum age cut-off point, the selection of children was done randomly. In Graissa, priority was given to the youngest girls in the list. In Nairobi, an additional household visit validated the vulnerability of the selected children. In all districts, the selection of beneficiaries was disputed due to the lack of transparency and clear identification criteria and processes.

During Phase 2 of the Pilot, a more clear process was defined. The Location OVC Committee (LOC), using a pre-defined form, provided a list of eligible households (poor taking care of OVC). With the clean list, enumerators went back to those households identified by the LOC as eligible, and collected more detailed information on the household, including a number of variables that were selected to reflect the household's welfare, and which were identified in focus groups with community representatives as well as through analysis using national household survey data. The program defined a poor eligible household as one that meets at least 8 out of 17 characteristics from among 9 different categories of household social-economic indicators.[1] With this approach, all variables were given the same weight in the selection process. This mechanism was implemented and its targeting effectiveness results of the mechanism was evaluated by the Oxford Policy Management group in 7 districts. Although the evaluation has shown that CT-OVC has successfully reduced poverty, improved food consumption and food diversity, increased school attendance potentially through reducing the need for child labor among the beneficiary households, the report also highlighted that "the main concern is that programme's poverty criteria were not effective in identifying the poorest households or at best moderately pro-poor".

An initial adjustment to the system was done in 2008. The forms and processes remained the same. However, as recommended by UNICEF ESARO, a poor eligible

[1] The 17 poverty characteristics are: (1) None of the adults in the household reached standard 8; (2) Caregiver is not currently working or s/he is working as a farmer or labourer; (3) Caregiver has less than two acres of land; (4) Construction materials of the walls is mud/cow dung or grass/sticks/makuti; (5) Construction materials of the floor is mud/cow-dung; (6) Construction materials of the roof is mud/cow-dung; (7) Toilet is of the type none/pan/bucket; (8) Source of drinking is water is river, lake, pond or similar; (9) Source of lighting fuel is firewood; (10) Source of cooking fuel is firewood or residue/animal waste/grass; (11) Owns no real state property here or elsewhere; (12) Owns two or less traditional zebu cattle; (13) Owns no hybrid cattle; (14) Owns five or less goats; (15) Owns five or less sheep; (16) Owns no pigs; (17) Owns no camels.

household was now to meet 10 out of the 17 characteristics (instead of 8 out of 17). In 2009, in order to increase the effectiveness of the selection beneficiary households, some additional changes were introduced to the same mechanism. Using the latest available national data, the 17 variables were given differential weights using the Proxy Means Testing and the weights were also estimated separately for urban, rural and Nairobi settings.

This note intends to put the targeting practice of CT-OVC into global context by briefly reviewing the various targeting mechanisms for cash transfer programmes and to compare and contrast the targeting accuracy and efficiency of the multidimensional poverty targeting approach, formerly employed in the programme and the current Proxy Means Testing approach.

Targeting Mechanisms in Cash Transfer Programmes

Targeting is a method that ensures the proper selection of beneficiaries of a program. It is a necessary step in non-universal cash transfer program in developing countries whose governments often are constrained by limited resources and torn between competing demands. There have been debate on whether targeting is worthwhile since it can be divisive among community members, highly complex in implementation, least applicable in a context of limited administrative capacity and unjustifiable in the presence of mass poverty of the population (Hanlon et al 2010). However, the general consensus is that better targeting can increase the cost-effectiveness of a program by channelling more benefit towards the poor within a fixed program budget (Coady et al, 2004).

Targeting can be conducted at various levels of analysis. When a cash transfer programme is designed, the first question comes to the policy-maker's mind is often which part of the country should the programme cover. This is called the geographical targeting in the literature. Another common method, categorical targeting, makes use of demographic characteristics of the population to target intended beneficiaries, e.g. pension benefits for people beyond a certain age or households with children under 5. However, the focus of this note is on individual/household targeting, i.e. how to select eligible beneficiaries from a given demographic group within a defined geographical location.[2]

There are six main mechanisms for identifying eligible beneficiaries. When complete information on a household's income and/or wealth is available and verifiable against independent and reliable sources such as pay stubs or income and property tax records, it is called **Verified Means Test** (Coady et al, 2004). Verified Means Testing is expensive and requires complete information from the tax system that are rarely available in the developing countries. Alternatively, a **Simple Means Test** can be conducted by programme staff through visits to the household to verify in a qualitative way that visible standards of living (which reflect income or wealth) are more or less consistent with the programme requirement. However, this approach is highly subjective and leaves discretion to the social worker or the programme staff that might be perceived as unfair or even as corrupted. The other extreme is to draw on existing knowledge about the poor and vulnerable within the communities in the absence of verifiable household poverty data in developing countries. Given the weak or absence of a functioning tax system and the relative closeness of communities, it is no surprise that **Community-based Targeting** is widely used in cash transfer programmes in Africa (World Bank, 2010). However, the community-based targeting is open to nepotism and elite capture while often erode cohesion and breed hatred within the communities (Hanlon et al 2010).

More recently, improved availability of national household economic/budget survey in developing countries and successful experiments in Latin American countries have given prominence to the **Proxy Means Testing** (PMT) approach even in Africa. Proxy Means Testing (PMT) use proxy indicators (readily observable and hard to manipulate), such as age, gender, state of housing, land access or labour availability to identify poor households (Slater and Farrington, 2009). First, weights of the proxy indicators are obtained by regressing the income/consumption of household on a whole set of household characteristics that correlate with income/consumption using nationally-representative household surveys. Second, weights from the multivariate

[2] We purposefully leave out the self-selection targeting method here since it is not commonly used for cash transfer programmes in Africa. Under self-selection, the cash transfer programme contains elements that encourage only the poor and vulnerable to access the programme's benefits as is common among public work projects, e.g. India's National Rural Employment Guarantee Programme.

regressions are applied to the sample of households under assessment to develop their PMT scores that are used to prioritize them. The advantage of this approach is that the ranking of the households is mechanical and objective and the focus on household assets rather than income limits the disincentive effect on work. The drawback of this approach includes lack of transparency and resorting to an impersonal "black box" (Hanlon et al 2010).[3]

A close relative of the PMT is the **Composite Wealth/Assets Index** approach. The index is normally generated through the Principle Component Analysis (PCA) or factor analysis using the same set of proxy indicators mentioned earlier.[4] Both are standard data reduction techniques that consolidate the asset variables into one measure that contains most of the variance in the data. For this school of thought, the income information available in household surveys—upon which a PMT is based—does not capture as adequately the permanent income status of rural households as composite wealth/assets index would (Ribas, Hirata and Soares, 2008). Examples can be found in Conditional Cash Transfer programs as well as other development policies (such as microfinance initiatives), in Peru, Colombia and Ecuador (Johannsen et al, undated). Although conceptually it makes sense to focus on the more stable long term income or wealth of the households as opposed to the highly volatile contemporary income, the calculation of the score remains a black box and what consist of assets will also vary from community to community and time to time.

More recently, **the multidimensional deprivation indexes** (MDI) are developed based on the theoretical foundation of Amartya Sen who argued that the study of poverty should focus, not on measuring income or consumption orexpenditure, but on the underlying capabilities without which it is not possible to live a full and

[3] Ways of improving the method includes using more up to date information to obtain new weights for the current models; (b) including socioeconomic variables that are more stable across time and are not easily manipulated by the informant and/or include geographical variables; (c) re-estimating the current models, differentiating the households' areas of residence to obtain different weightings for each; (d) modifying the cutoff points to an acceptable leakage level; (e) using other estimation methods for the models (for example, logistical instead of discriminant analysis) or modifying the dependent variable in current models (for example, income instead of poverty status); (f) improving the quality of potential beneficiary information used to estimate scores; among others.

[4] In fact, the composite index approach is subsumed under the PMT in the review of targeting mechanism review by Coady et al, 2004.

meaningful human life.[5] For proponents of the MDI, income is only one dimension of human capabilities and the other dimensions are important in their own right regardless of their explanatory power on income or its long term manifestation, assets. Sen's capability approach has given rise to a booming field of multidimensional deprivation. It has been applied to a wide range of themes: quality of education, child and youth poverty, governance and political freedom, social responsibility, gender inequality in human development, and the targeting of social programmes. UNICEF has been a pioneer in this field and firmly supports measuring child poverty through a multidimensional lens as exemplified by the Bristol approach and the ongoing Global Study on Poverty and Disparities in 48 countries. [global study website]

Yet the methodology does not give clear prescriptions on the selection of dimensions and assignment of weights across dimensions when a composite index is calculated based on the capability approach. The selection of dimensions is not a question unique to the MDI though. Both composite index and PMT approach face similar challenges. With regard to the assignment of weights across dimensions, the other two approaches are able to generate specific weights taking advantage of data mining. Sen argued that relative weights between dimensions should reflect value judgments and these value judgments should be made explicit and subject to public scrutiny and improvement over time. This normative weight across dimensions is difficult to implement in practice. In reality, practitioners of MDI resort to equal weight for dimensions. From 2002, India identified rural households as 'below the poverty line' (BPL) according to a 13-item comprising topics such as food, housing, work, land ownership, assets, education, and so on in the census questionnaire.[6] The 13 dimensions are given equal weights in calculating the total number of deprivations of a household. In Indonesia, households are classified into five welfare status and a household is classified as a poor household if it fails on any of the following five conditions: (i) all household members practice their religious obligations; (ii) all household members eat at least twice a day; (iii) all household members have different set of clothing for work, school, visit; (iv) the largest part of house floor is not made of earth; and (v) sick

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6 Depending upon the response category selected, the household is assigned a score (0-4) for each variable. A household's score is then summed to create an aggregate score. A poverty cutoff is fixed at the State level or at lower levels for the aggregate score. Households falling below that area's cutof are identified as 'BPL' (Alkire and Seth, 2009).

household members and contraceptive users use modern medical service (Suryahadi and Sumarto, 2003).[7] To reach the highest welfare status, a household has to pass a total of 22 indicators. For believers of PMT, the MDI applies equal weight while clearly the proxy variables of income have differential explanatory power for income. Currently, Mexico's National Council for Evaluation of Social Development Policy (CONEVAL) is defining a multidimensional poverty model and is pilot-testing a related targeting instrument (Johannsen et al, undated). The presentation of various targeting approaches begs the question that how to evaluate the performance of them, which is the focus of the next section.

Performance of Targeting Measure for Cash Transfer Programmes

- A common approach to evaluate the targeting performance of alternative transfer instruments is to compare undercoverage and leakage rates (Coady et al, 2004). Undercoverage is the proportion of poor households that are not included in the program (errors of exclusion). Leakage is the proportion of those who are reached by the program who are classified as nonpoor (errors of inclusion).
- Targeting trade-off: generally speaking, actions taken to reduce one kind of error may cause the other to increase. Introducing more stringent rules in order to screen out the nonpoor will raise the risk of leaving the poor out as well. Thus, while meant to reduce errors of inclusion, it will also heighten errors of exclusion. Similarly, raising the cut-off point in an (imperfect) proxy-means score or multidimensional deprivation index in order to reduce undercoverage will also tend to increase leakage.
- Methodological inconsistencies: A practical question that arises when one tries to measure targeting performance is how to define the criteria. The most popular criterion in the literature is headcount income (consumption) poverty or food (extreme) poverty. Paradoxically, these practices are inconsistent with the MDI and Composite Asset/Wealth Index approach because both argue that

[7] The Family Planning Coordinating Board (BKKBN) Indonesia classified all households in into five welfare status: (i) Pre-Prosperous Households (*Keluarga Pra Sejahtera* or KPS), (ii) Prosperous Households Level I (*Keluarga Sejahtera* I or KS I), (iii) KS II, (iv) KS III, and (v) KS III+. Poor households are often equated as the KPS households, but sometimes they are defined to include the KPS and KS I households.

the poverty measurement and consequently the poverty targeting go beyond contemporary income. Yet the targeting performance of these two approaches is still evaluated against monetary reference criteria with respect to the monetary poverty line using exclusion and inclusion errors (Johannsen et al, undated).

Coady et al (2004) review the experiences with the targeting methods using in cash transfer programmes in developing counties and find that targeting in developing country context can work but not always. First there is no one clearly preferred method or system which will work in all countries all the time. Second, the best performers are individual means tests, followed by characteristic (or categorical) targeting and then self-selection. Third, there is extremely large variation in performance within each type of targeting method, including the proxy means tests popular in Latin America, leading the authors to conclude that the most important determinant of targeting success is the implementation capacity specific to the programme (Handa and Davis, 2006).

Kenya is a good case in point. In the next two sections, we will briefly review the evolution of targeting approach in Kenya's CT-OVC programme and then compare the performance of the two households targeting approaches: MDI and PMT, used in Kenyan programme

Targeting Approach in Kenya's CT-OVC Programme

Over the years, the CT-OVC programme has used a combination of targeting methods to refine its targeting. In the pre-piloting phase (2004-2005), only community based targeting was used drawing on the knowledge of members of Local OVC Committees. As the programme expanded, so was the need to identify additional districts other than the first three which were selected out of convenience since UNICEF had existing programmes there. 69 districts were ranked according to the number of extreme poor households taking care of OVCs using the Kenya Integrated Household Budget Survey (KIHBS 2005/06) data, and priority was given to districts with the highest number of extreme poor OVC households.[8] The 1999 census data were used to further rank the locations within each district according to the number of OVC households per location. The programme was not intended primarily to address poverty. Nevertheless, the programme decided to prioritise support to poor OVC household due to limited resources (Oxford Policy Management, 2010). The poverty targeting criteria was first verified using a multi-dimensional deprivation approach in 2006 and replaced by a PMT developed jointly by the government and the World Bank in 2009 (Oxford Policy Management, 2010 and Aide Memoire, 2010).[9] This study focuses on the comparative targeting accuracy of these two approaches.

The following is a brief description of the household targeting process used for the CT-OVC Programme which consists of a five-step process:[10]

1. The first step of the household targeting is the listing of eligible households (through Form 1), meeting the following three criteria; 1) has permanent members who are OVC; 2) is extremely poor; and 3) does not benefit from other similar programs.

    - An OVC is a child (<18 years old) who complies with at least one of the following: (i) has lost one or both parents (i.e., single/double orphan); (ii) lives in a household where at least one parent, caregiver or child was chronically ill (chronically is defined as a caregiver or child who was been bedridden for at least the last 3 months and has a terminal illness , i.e. HIV/AIDS, tuberculosis, cancer); (iii) lives in a child-headed household (where the caregiver is < 18 years old).
    - Poor households: For the case of identifying poor households, the LOC should gather information for Form 1 only from households who they believe are extremely poor from a variety of dimensions. This information will guide the LOCs to

[8] The 69 districts are based on the old district division in Kenya.
[9] See introduction for more detailed description of the evolution of the targeting approach in CT-OVC.
[10] This section draws heavily on the Aide Memoire after the Joint Review and Implementation Support Mission comprise representatives of the Government of Kenya and the Development Partners, including DFID, SIDA, UNICEF and World Bank.

determine the poverty status and the consequent eligibility of a household.[11]

- Beneficiary of other programmes: If the LOC finds households currently enrolled in any similar programme or receiving any external support, they should not be selected for the Programme.

Once the information is collected in the field, decisions are made on eligibility for each "identified household". The listings of households are sent to the District Children's Officer (DCO) and eventually to the OVC Secretariat in the Ministry of Gender, Children and Social Development (MGCSD) for another round verification in the Management Information System.

2. The second step of the household targeting is to verify the information collected by the LOCs (list of eligible households) through Form 2. The enumerators return to the eligible households (identified through Form 1) to collect data for Form 2. The information collected in this step has three purposes: (i) confirm that the families contain at least one OVC; (ii) collect additional household members' characteristic data; and (iii) collect additional poverty parameters of the household. [12]

3. The third step of the household targeting is to verify the quality of data in Form 2 by the District Children's Officer (DCO), District OVC Sub-committee (DOSC) and the MIS team at the OVC Secretariat.

4. The fourth step of the household targeting is to enter the data from Form 2 and apply the multidimensional deprivation approach or the PMT to determine which households qualify for the Programme using the

[11] (a) Caregiver is unemployed or not having regular income; (b) Adult members in the household having current difficulties to find a daily paid job; (c) No house/land ownership; (d) No heads of cattle, pigs, chicken and/or goats; (e) No access to safe drinking water; (f) Floor, roof and walls made of mud/cow dung/grass/sticks/makuti; (g) The household lacks any assets besides a place to sleep; (h) Children of the household not attending school because of lack of materials/uniforms or helping parents/caregivers to meet daily food needs; (i) The family members wear much deteriorated clothes; (j) The health condition of household members is evidently very weak; (k) The sanitary conditions of the household are very poor; (l) Number of meals per day (1 or less = poor); (m) Other reasons identified, please specify the reason.

[12] See footnote 1.

information collected in Form 2. The poverty targeting was first based on the multidimensional deprivation approach with any household exhibiting eight or more of these characteristics out of 17 characteristics being classified as poor (see footnote 9). However, the CT-OVC evaluation baseline report (2008) commissioned by UNICEF and conducted by Oxford Policy Management showed that this initial poverty test was not effective at identifying poor households. As a result the poverty test has been revised, employing an allegedly more sophisticated proxy-means test approach based on the 2005-06 Kenya Integrated Household Budget Survey (KIHBS). The PMT is applied to all households and all households below the cut-off point of the PMT enter into the Programme, unless the total number in a district exceeds the planning target. If this is the case, priority is given to child-headed households. Once the child-headed households have been selected the remaining households are ranked according to the PMT score and those with the lowest PMT score are selected up to the budget ceiling.

5. The fifth step of the household targeting process is community validation. The list of the potential beneficiary households is presented and approved in a public *gathering/baraza* organized by the DCO and DOSC members. The final list is then sent to the OVC Secretariat for adjustment in the MIS (if necessary). The OVC households on the approved beneficiary lists are later enrolled into the Programme.

Data

This paper uses the 2005/2006 Kenya Integrated Household Budget Survey (KIHBS) data collected by the Kenya National Bureau of Statistics and the Planning Unit of the Ministry of Planning and National Development. The survey was conducted using the National Sample and Evaluation Programme (NASSEP) frame which is based on a two-stage stratified cluster design for the whole country. First enumeration areas using the national census records were selected with probability proportional to size of expected clusters in the enumeration area. The number of expected clusters was obtained by dividing each primary sampling unit into 100 households. Then clusters were selected randomly and all the households enumerated. From each cluster, 10 households were drawn at random. Data was collected from a sample of 13,430 households drawn from 1,430 clusters from 70 districts. The survey collected information on different modules, covering all possible socio economic data requisite for analysis of household welfare and social protection. The household questionnaire consisted of 21 integrated modules designed to collect information on the following: demographics; education; health; employment; fertility and mortality; labour; child health and nutrition; housing; water, sanitation and energy use; food consumption and expenditures; non-food consumption; ownership of durable goods; agricultural holdings, activities and outputs; livestock; household economic enterprises; transfers; income; credit; and recent shocks to household welfare.

Simulating the Targeting Performance of MDI and PMT Approach in Kenya's Context

In this section, we simulate and compare the targeting performance of the multidimensional deprivation index and Proxy Means Test, two approaches used in the targeting of Kenya's CT-OVC programme. While we are aware of the methodological inconsistencies using the exclusion and inclusion errors raised earlier, there is no other alternative approach for targeting performance in the literature. Therefore, we follow the earlier literature in evaluating the targeting performance. The question we try to answer is that leaving aside the philosophical differences, how the MDI fares compared with PMT? Specifically, we compare the monthly per capita expenditure of eligible and ineligible households identified by the MDI and PMT approach to the poverty line and food (extreme) poverty line to get at the inclusion and exclusion errors, using the Kenya Integrated Household Budget Survey (2005-2006). The data is stratified into rural and urban sample because poverty line is calculated separately for rural and urban Kenya to reflect the differential living cost.

We first compare the two variations of MDI and PMT used in the CT-OVC (see section 3.4 for details). For the MDI approach, any household exhibiting eight or more of these characteristics out of 17 characteristics are classified as poor and identified as eligible for the programme. Following the joint efforts of the Government of Kenya and the World Bank to develop PMT, PMT is applied to rural and urban households separately with similar proxies and specifications. An important difference for the rural and urban estimation is that the livestock information is not included in the urban sample. Once a household's PMT score is calculated based on the coefficient estimates from the multivariate analysis, cutoffs are drawn at poverty and food poverty line to identify eligible households.

Table 1. Targeting Performance of MDI and PMT: Kenya's CT-OVC

	Rural Sample				Urban Sample			
		MDI 8	PMT Cutoff 1	PMT Cutoff 2		MDI 8	PMT Cutoff 1	PMT Cutoff 2
Poverty Line	Inclusion error (%)	39.56	27.47	12.63	Inclusion error (%)	23.44	21.92	2.64
	Exclusion error (%)	17.49	27.9	49.38	Exclusion error (%)	35.87	20.4	48.26
Food Poverty Line	Inclusion error (%)	67.49	58.37	38.53	Inclusion error (%)	62.57	66.17	32.26
	Exclusion error (%)	5.87	9.01	22.57	Exclusion error (%)	7.92	1.76	14.13

Table 1 shows that for rural sample of KIHBS, PMT consistently outperforms MDI with smaller inclusion error but at the same time, has higher exclusion error. The same comparison holds for urban sample when PMT cut-off is set at the food poverty line. However, when PMT cut-off is set at the poverty line, the PMT performs as good as the MDI on inclusion error while outperforming MDI on exclusion error. There is no clear-cut conclusion on the dominance of either approach.

We also explore another counting method after the total number of deprivations and the PMT score are produced from the MDI and PMT approach respectively. Instead of setting the cut-off for MDI at a minimum of eight deprivations and for PMT at poverty or food poverty line, we sort the households by their the total number of deprivations (ascending) and their PMT score (descending) and identify the bottom 10% household as the targeted group. Table 2 shows that PMT perform as good as the MDI on exclusion error while outperforming MDI on inclusion error. It seems that the

PMT approach has a distinct advantage when we use the bottom 10% counting approach which is quite common in the cash transfer programmes.

Table 2. Targeting Performance of MDI and PMT: new targeting rule for Kenya's CT-OVC

		Rural Sample			Urban Sample	
		MDI Bottom 10 pct	PMT Bottom 10 pct		MDI Bottom 10 pct	PMT Bottom 10 pct
Poverty Line	Inclusion error (%)	30.81	7.45	Inclusion error (%)	8.41	3.2
	Exclusion error (%)	55.08	52.69	Exclusion error (%)	48.02	49.46
Food Poverty Line	Inclusion error (%)	55.89	27.7	Inclusion error (%)	39.9	32.03
	Exclusion error (%)	28.26	25.34	Exclusion error (%)	14.84	15.34

Yet the comparison so far is biased towards the PMT approach because it has been improved with regression analysis specific to context of urban and rural areas of residence. However, we assume that the MDI approach will use the same identification for urban and rural areas alike. In this section below, we redo the simulation distinguishing the identification of eligible urban households by dropping the livestock and lands proxies as they are not applicable to urban settings. Results are presented in Table 3 and 4 where the only difference between them and Table 1 and 2 respectively is the column titled "MDI8" for the urban sample. MDI approach in Table 3 performs better than before the adjustment in Table 1 with significant reduction in inclusion errors at the expense of minimal increase in exclusion errors. When we use the bottom 10% approach, MDI approach has flipped its advantage and disadvantages in exclusion and inclusion errors relative to performance before the adjustment in proxy variables. Another important finding is that PMT has lost its dominance in performance as evident in Table 2 before the adjustment.

Table 3. Targeting Performance of MDI and PMT: Kenya's CT-OVC with updated proxies in urban sample for MDI

	Rural Sample				Urban Sample			
		MDI 8	PMT Cutoff 1	PMT Cutoff 2		MDI 8	PMT Cutoff 1	PMT Cutoff 2
Poverty Line	Inclusion error (%)	39.56	27.47	12.63	Inclusion error (%)	10.62	21.92	2.64
	Exclusion error (%)	17.49	27.9	49.38	Exclusion error (%)	44.3	20.4	48.26
Food Poverty Line	Inclusion error (%)	67.49	58.37	38.53	Inclusion error (%)	46.46	66.17	32.26
	Exclusion error (%)	5.87	9.01	22.57	Exclusion error (%)	12.16	1.76	14.13

Table 4. Targeting Performance of MDI and PMT: new targeting rule for Kenya's CT-OVC with updated proxies in urban sample for MDI

	Rural Sample			Urban Sample		
		MDI Bottom 10 pct	PMT Bottom 10 pct		MDI Bottom 10 pct	PMT Bottom 10 pct
Poverty Line	Inclusion error (%)	30.81	7.45	Inclusion error (%)	42.36	3.2
	Exclusion error (%)	55.08	52.69	Exclusion error (%)	21.59	49.46
Food Poverty Line	Inclusion error (%)	55.89	27.7	Inclusion error (%)	2.99	32.03
	Exclusion error (%)	28.26	25.34	Exclusion error (%)	76.9	15.34

6. Conclusion and Discussions:

The paper simulates the targeting performance of the Multidimensional Deprivation Index and Proxy Means Test approach using Kenya Integrated Household Budget Survey and the institutional setup of the Cash Transfer for OVC in Kenya. It reaffirms the earlier finding in the literature that there is no one preferred method or system when it comes to targeting eligible households. When we simulate the targeting performance of the MDI and PMT approach used previously and currently in the CT-OVC programme in Kenya, it seems that PMT consistently outperforms MDI with smaller inclusion error but under most circumstances has higher exclusion error. When the bottom 10% counting approach is used., PMT approach has a seemingly distinct advantage over MDI for both rural and urban samples. However, this seemingly advantage of PMT turns out to be an artefact of the way we compare the PMT with MDI. We are comparing a PMT approach that has been customized to urban settings with a MDI approach without the necessary adjustment. Once the approaches are comparable, estimation results show that there is no discernable pattern on the relative advantage and disadvantage of them.

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