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MASTER THESIS

Assessing the Effectiveness of Proxy Means Testing in Targeting:

A Case Study of Kenyan Cash Transfer for Orphans and Vulnerable Children

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Declaration

I, Amna Babar, hereby, declare that the Thesis entitled 'Assessing the Effectiveness of Proxy Means Testing in Targeting – A Case Study of Kenyan Cash Transfer for Orphans and Vulnerable Children', submitted to the GLODEP Consortium 2020, is my original work, and any theoretical and empirical literature and dataset used in the proceedings of this study have been duly cited and referenced.

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Zásady pro vypracování

Targeting is a process that spans, not just the very initial phases but the entire life of an aid project. Answering the questions of 'where', 'when' and more importantly 'who' should be receiving food aid or assistance, targeting plays a pivotal role in determining the effectiveness of these aid modalities. While the contribution of Christopher Barret in literature gives a decent theoretical basis to the issue, Annual Review of Targeting reports by ECHO and WFP combined with UNHCR databases help to give an empirical understanding of the persistent challenges faced by donors and developing agencies to accurately identify and reach intended beneficiaries. Moreover, the scarcity of food aid and per dollar value increase with effectiveness of targeting not only highlight the importance of targeting mechanisms but also bring attention to the 'revision' of these mechanisms in order to operationalize updated techniques because of changes in household characteristics and/or model recalibration. Since targeting is a multi-layered process (at geographic, household or individual level) carried out by different mechanisms (administrative, community based and self-targeting), a variety of econometric tools are used to capture these dimensions. As Vulnerability Analysis Mapping (VAM) and Proxy Means Testing (PMT) remain two of the most popular econometric modeling techniques for targeting anti-poverty and aid programs, this research aims to address the 'cracks' i.e. the inclusion and exclusion errors of these techniques during implementation to improve ex-ante aid targeting for increased effectiveness.

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Abstract

While universal provision of services and assistance has placed nation-building at heart in different countries for many years, very often than not, this provision is stratified to the most powerful, and marginalizes large populations of the needy and poor. This gives rise to the need of devising, implementing and evaluating mechanisms to ensure that the poor indeed benefit, namely from the mechanisms of 'targeting'. Answering the questions of 'where', 'when' and more importantly 'who' should be receiving assistance, targeting plays a pivotal role in determining the effectiveness of different assistance transfer modalities. This study reviews the various techniques of administrative and community based targeting at household and individual level and focuses on the econometric tool of Proxy Means Testing (PMT); with the primary objective of understanding the methodological discretions in the technique and their impact on its effectiveness.

Using the updated dataset of Kenyan Integrated Household Budget Survey 2015/16, a PMT simulation is run for the country's cash transfer program for Orphans and Vulnerable Children (OVC) at different poverty thresholds by employing Ordinary Least Squares. The results indicate that targeting through proxy means testing performs markedly better than universal transfers and is significantly progressive in both, incidence and coverage. It is also encouraging to note that proxy means testing helps eliminate as much as 50% of inclusion errors otherwise implied by including all OVC households in the program. This, however, comes with a repeatedly emphasized trade-off with a large number of households incorrectly excluded from being selected as eligible for the transfer. It is therefore a policy matter and future research contributions on conducting an ex-poste analysis of actual beneficiaries of OVC-Cash Transfer can help modify the welfare proxies and increase the predictive power of proxy means tests as a targeting tool for the program.

Keywords: targeting; proxy means test; incidence; coverage; inclusion error; exclusion error.

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List of Abbreviations

CBT	Community Based Targeting
CCT	Christian Council Of Tanzania
DHS	Demographic Health Survey
FAO	Food and Agriculture Organization
HBS	Household Budget Survey
HSNP	Hunger and Safety Net Program
KIHBS	Kenyan Integrated Household Budget Survey
KNBS	Kenyan National Bureau of Statistics
LOC	Local OVC Committee
LSMS	Living Standards Measurement Study
MDI	Multi-Dimensional Poverty Indication
MENA	Middle East and North Africa
ODI	Overseas Development Institute
OLS	Ordinary Least Squares
OVC	Orphans and Vulnerable Children
PLS	Poverty Weighted Least Squares
PMT	Proxy Means Testing
PNSP	Productive Safety Net Programme
UNICEF	United Nations International Children's Emergency Fund
UNHCR	United Nations Higher Commissioner for Refugees
WFP	World Food Program

Chapter 1. Introduction

Universal provision of any form of national or international assistance has placed the ideological reasoning of nation-building and equality-for-all at heart for many years. Many “late industrializers” also indicated that it is indeed an important ingredient for the achievement of higher levels of growth and social development in these countries (Mkandawire, 2001). However, with such ‘universalism’ being stratified towards most powerful and larger shares of population being marginalized (Manow 2001: 95), the poor or less privileged have only seen to receive the trickle-down effects of such assistance. Consequently, the last two decades of 20th century saw the emergence of, and support for, mechanisms to direct these transfers especially to the ‘poor’. Moreover, limited fiscal budgets and debt crisis of 90s shifted the debate between universalism and targeting to the language of ‘efficiency’ wherein per dollar increase in the value by aid and assistance modalities became imperative in deciding their allocation. Consequently, while the subject dominated academic debates in the 80s and 90s; empirical examples of different targeting mechanisms emerged as national governments and international actors took it upon themselves to not only devise but to also implement and evaluate ways to ensure that the poor benefit. A process that spans not just the start but the entire life of an assistance program or an aid transfer, targeting mechanisms include administrative and self-targeting as well as participative approaches of community based targeting.

This study aims to review different targeting mechanisms with a particular focus on the econometric targeting techniques to assess the magnitude and impact of the “cracks” or errors in such methods. The initial motivation of this dissertation had been to assess the effectiveness of these targeting methods in the context of food aid, for an ex-ante analysis of an assistance project by World Food Program and its beneficiaries coupled with refugee databases of UNHCR to evaluate the coverage and effectiveness of targeting employing Proxy Means Testing (PMT) and Vulnerability Assessment Mapping(VAM). However, under the unforeseen circumstances of COVID-19 becoming a global pandemic when this dissertation has been written, the constraints to not only the physical mobility made it impossible to collect the desired data but the atypical functioning of these organizations under lockdown resulted in the inability to reach out to them requesting remote access. Consequently, an entire completed subsection of review of literature on food aid driving the initial motivation was removed and instead the entire focus was redirected to evaluating the effectiveness of Proxy Means Testing on an available dataset for a social safety program instead of a humanitarian assistance project. This is because while administrative data from the highlighted organizations was needed for the former, a simulation for the later could be made possible by the use of household surveys.

The focus of this study, nonetheless, remains on the econometric targeting method of Proxy Means Test which is a tool to predict welfare when reliable data on income is not available or is very costly to collect. Initiated in Chile and widely applied in various social assistance programs in Latin America (Lindert, 2006**)**, targeting through proxy means testing gained popularity particularly in designing and implementing cash transfers in Africa and South-Asia. As most of the initial literature on PMT targeting presents a geographical focus on Latin America and later on South Asia, Africa poses a particular point of interest. Therefore, employing a pragmatic approach, this dissertation chooses Kenya to do a predictive exercise and add to the analysis conducted by Brown and Ravallion (2016) on nine African countries of Burkina Faso, Ethiopia, Ghana, Malawi, Mali, Niger, Nigeria, Tanzania and Uganda**.** Moreover, it does so by choosing the cash transfer program of Kenyan government directed at Orphans and Vulnerable Children (OVC) as a case study to highlight the importance of dimensions of vulnerability including but not limited to monetary poverty. This is so because not only is OVC the largest cash transfer program in Kenya, proxy means testing has been proposed as a solution in the program's baseline evaluation in 2008 (Hurrell et al., 2008) to the targeting ineffectiveness of the initial poverty-scorecard used in the program. However, this has so far been done using data from Kenyan Integrated Household Budget Survey of 2005/06. This study, hence aims to add value to the existing literature on PMT analysis of OVC-Cash Transfer to simulate operationalizing updated targeting because of changes in household characteristics and/or model recalibration using the updated dataset of KIHBS 2015/16.

The main focus of this targeting simulation is to assess PMT as a methodology by evaluating the incidence and distribution of the inevitable targeting errors of inclusion and exclusion that form the most popular criticism of using predicted instead of actual data on income and consumption.

Chapter 2 covers the review of theoretical and empirical literature on various targeting methods and an additional Chapter 3 has been added to place the study in the context of the chosen country of Kenya and OVC-Cash transfer as a particular case study in face of redirecting the initial topic for this dissertation. Chapter 4 explains the data design and methodology along with the descriptive statistics of sample population while Chapter 5 discusses the main results and proposes extensions to the basic PMT model employed. The dissertation closes with the final Chapter discussing the conclusions and recommendations for the way forward.

Chapter 2 : Literature Review

The following chapter traces the origin of and tracks the debate on the subject of targeting, from the academic literature through to the empirical analysis by different national and international actors. This research draws from the theoretical literature while expanding the review of empirical studies to both food and cash assistance for a better understanding of targeting mechanisms over different countries and in different contexts.

Although the reviewed literature aims to cover most targeting techniques, the most popularly used method of Proxy Means Testing approach is particularly highlighted in country case studies. This is done in order to identify gaps or challenges in this econometric method that can possibly be filled by borrowing from and incorporating the likes of more participatory approaches that are recently attracting donor attraction.

2.1. Theory of Targeting

While universalism and its merits have long occupied a position of favor in theoretical and empirical literature in development, it was well in 20th century that the counter approach of "targeting" emerged as a popular conceptual case. Moreover, the debate has been as controversial in developed countries as it is in the developing ones (Mkandawire, 2005). Initiating primarily in the field of social protection programs the provision of equal protection to all (universalism) posed serious fiscal constraints and therefore pivoted the debate in the language of efficiency. Moreover, the context of 'aid fatigue' quickly made not only policy makers but also international actors to explore and increasingly adopt the principle of targeting. Where the social returns for a given level of transfers became established to be higher for individuals or households at the lower end of the income distribution, the fiscal crises of the 1980s further questioned the viability of universal provision of social policy and led to a breakdown of some of the social pacts that had sustained universalism. On the other hand, parallel to a shift towards targeted assistance nationally to combat poverty, inequality and insecurity, the evolution in science of international humanitarian assistance in the face of dire crisis also gained support for requiring more targeting (Verme & Gigliarano, 2019).

Ethiopian guidelines by Clay et al. (1999) reason three different grounds for targeting namely humanitarian, resource and efficiency, and development reasons. Similarly, Emergency Nutrition Network Report by Save The Children lists four reasons of targeting, namely need assessment, avoiding harm, efficient resource allocation and relief food (Taylor & Seaman, 2004). As these reasons motivated the discussion on targeting among national and international policy makers, different definitions of targeting emerged. With a general consensus of the definition of targeting, applied to food as well as non-food aid, it is defined as the process by which areas are selected to receive emergency food aid and then provided with it (Clay & Stoke, 2000). Similarly, Seaman & Taylor (2004:4) highlighted it as "directing a particular type or quantity of food, to a defined population group" while Barret & Maxwell (2005) highlighted targeting as ensuring the assistance reaches people who need it, when and where they need it, in an appropriate form, in appropriate quantities and through effective modalities – and conversely does not flow to people who do not need it.

WFP (2006) establishes basic principles to guide decision making in a range of emergency situations drawing on decades of experience of WFP and its partners and breaks down the process of targeting in two different steps: i- identifying and selecting communities in need ii- delivery and distribution.

2.2. Targeting Methods

2.2.1. Main Approaches

Dissecting further into different approaches of 'how' targeting can be done, generally there are three broad approaches or methods: administrative targeting, self-targeting and more recently, community based targeting (Maxwell et al., 2011). While decision-makers generally external to the community set a criterion to identify the target population based on assessment of indicators in administrative targeting, participation is left to the discretion of individual/household in self-targeted programs. Besides, in community based targeting, the recipient community defines the criteria and validates who qualifies. The subsections that follow discuss these methods in further detail.

FAO (2001) instead defined targeting mechanisms essentially as being either administrative or self-targeting wherein the former encompasses targeting through regions or identification of households/individuals through different econometric techniques or through involving community leaders (hence merging community based targeting).

Targeting can also be a multi-stage process. Once the regions or communities are identified, specific individuals/households within these communities are identified as intended beneficiaries for assistance. Somewhat integrating these layers of the targeting process, Coady et al. (2004) classify targeting methods by distinguishing between 'methods' and 'actors' in their comprehensive book reviewing targeting of transfers in developing countries. Where 'methods' refer to approaches taken to target a particular group, the book refers to 'actors' to identify individuals and agencies who perform the implementation. Highlighting that targeting is a multi-layered process instead of an activity; Coady et al. (2004) define three broad groups and techniques to target these broad groups as illustrated in Table 1.

Table 1.

Level and type of different targeting methods

Level	Type
Categorical	Geographic Demographic (gender, age)
Individual/Household Assessment	Means Test Proxy Means Test Community Assessment
Self-Targeting	Work Consumption

Note. Adapted from Coady et al.(2004)

The current research narrows down the focus on the particular layer of individual/household identification within broadly defined targeted populations to improve the effectiveness of assistance. The following section reviews Means Test, Proxy Means Test and Community Based Targeting/Assessment following Coady et al., (2004)'s approach. In addition, a review of Self Targeting is also presented below, however as only limited to its use in household/individual identification as warranted by the scope of this research.

Moreover, it is important to note that the above mechanisms are not mutually exclusive techniques and can be used in different combinations and sequences. Different actors and methods can overlap i.e. an external decision-making agency (administrative targeting) can in fact employ means testing (individual assessment) in poor neighborhoods (geographic targeting). Coady et al., (2004) exemplify 253 occurrences of different targeting methods out of which just 48 use a single targeting method, while the rest use a combination of two or more methods (42 use two methods, 21 use three methods and 11 use four methods).

2.2.2. Errors in Targeting Methods

It is equally highlighted in theory and in practice that each of these targeting methods discussed in further detail below suffer from inevitable trade-offs that cannot be fully resolved. These techniques rank on a continuum of the being most information intensive but at the same time demanding the highest strain on resources. Proxy Means Test and Community Based techniques, for instance, veer to opposing extremes on the transparency/access to information scale; one relies on excessive information and offensive transparency, while the other relies on insufficient information and deliberate obfuscation.

The errors and the subsequent consequences include not only operational difficulties and context-specific implementation challenges but also some built in errors of targeting methods amongst which most important and widely analyzed are Inclusion and Exclusion Errors. Inclusion Error is defined when a targeting technique incorrectly selects non-poor as the beneficiaries of assistance whereas exclusion error occurs when the needy and poor are incorrectly missed out in the selection of beneficiaries. The distinction between these two errors dates back to Weisbrod (1970) who referred to them as measures of 'vertical and horizontal targeting efficiency'. While Smolensky et al., (1995) called them as 'errors of inclusion' and 'errors of exclusion' primarily in the macroeconomic adjustments in Latin America, the terms were adopted in the development sector by Cornia & Stewart (1993) in their detailed study of the food intervention programmes. They found that most of the imperfections common to all these problems could be brought under two headings to which they gave the title of "Two Errors of Targeting".

2.2.3 Targeting Methods and International Actors

A key observation drawn from literature and highlighted by UNHCR, WFP (2015) in the review of targeting methods for Syrian refugees in Jordan, Lebanon and Egypt, is also the approach of different international actors towards the targeting errors. While WFP starts from blanket coverage and then aims towards reducing inclusion errors; UNHCR approaches this from the opposite direction and focuses on exclusion error minimization.. In this way, conceptually the World Bank, UNHCR, and WFP analyze the same thing but through different angles as discussed below.

Despite the substantial overlap and benefit of joint data collection, the analytical methods differ greatly. While targeting of food aid benefits from decades of experience by WFP's Vulnerability Assessment Mapping (WFP, 2014), UNHCR employees econometric analysis techniques (primarily PMT) with particular support from The World Bank in MENA region. WFP studies seem to be more familiar and comfortable with consumption scores or indicators like food consumption scores, dietary diversity indexes and food frequency indexes while UNHCR prefers case-by-case approach.

2.3. Empirical Evidence of Targeting Methods

The following section below closes the loop by focusing on household/individual identification techniques with particularly expanded empirical evidence on the most commonly used econometric technique of Proxy Means Test with brief descriptions of the targeting techniques and of multiple aspects linked to the subject above.

2.3.1 Means Testing

The gold standard in targeting is means testing when direct assessment of households' characteristics is used to identify eligibility (Coady et al., 2004). This information provided by the applicant is then verified from third parties (often income and tax records). Office or house visit to assess the household's living standard may also be used as verification. Grosh (1992), for instance, accounts that the reported information by an applicant needed to be signed by a community representative.

However, the effectiveness of means testing is highly reliant on the ability to collect and verify the information on income and living standards at a reasonable cost. Moreover, as income is the criteria for this targeting technique, Dilnot & Stark (1989) point out the possible downside of creating disincentive for applicants to earn own income as households in the UK found themselves in poverty traps. Since this technique requires high administrative capacity and is appropriate only when income/welfare are easily declared and verifiable, the cost for means-testing is often not justified in humanitarian assistance programs (Kidd& Gelders, 2017).

2.3.2. Proxy Means Testing

Proxy Means Testing is employed wherein a 'score' for each target population unit is calculated on a small number of easily identified and quantifiable proxy welfare indicators. The methodology has managed to gain powerful advocates with publications like del Ninno and Mills by the World Bank (2015) about safety nets in Africa and Leite (2014) promoting that PMT can accurately target the chronic poor.

The first step in the method is to select some easily observable and feasible variables that correlate with poverty/deprivation and are difficult to manipulate through an iterative process that evaluates their predictive power. The choice of these proxy variables is then followed by comprehensive statistical analysis to assess the strength of correlation of each variable with household income to derive an appropriate weight, leading to the calculation of a 'score' for each household/applicant. This calculated score is then compared against a predetermined cut-off/eligibility criteria to differentiate the poor from non-poor. The most common approach towards proxy means testing is the application of Ordinary Least Squares (OLS) as shown by Glewwe & Kanaan (1989), Grosh & Baker (1995), Narayan & Yoshida (2005) and Ahmed & Bouis (2002) to point out a set of variables that are able to proxy for welfare. Other less often techniques to determine these weights include principal component analysis or quantile regressions (Koenker & Basset, 1978).

Many a times, these variables are not revealed to the target population in order to prevent the moral hazard of information manipulation (UNHCR, WFP 2015). Lessons from cash transfer programming for Syrian refugees in southern Turkey (Armstrong & Jacobsen, 2015) highlight some ways to minimize this while also addressing the frustration that participants exhibit towards this information asymmetry. By developing a quantile regression PMT model for Africa, Brown et al., (2018) find out that in comparison to the counterfactual of uniform allocation, PMT allows for a substantial reduction of inclusion errors. This is also one of the methods thoroughly discussed by Mills et al., (2015) in particular reference to Sub

Saharan Africa wherein after doing ex-ante simulations for seven country specific case studies, the authors concluded that PMTs generally perform well in Sub Saharan countries.

The implications and consequences of using different cut-offs on the effectiveness of PMT are highlighted in empirical evidence below.

PMT Case Studies

First used in Chile in 1980, Proxy Means Testing has since then been widely used not only in other Latin American countries – Colombia (Castaneda, 2003) and Mexico's PROGRESA (Coady, 2001; Skoufias et al., 1999) – but all over the globe. An earlier comparative study by Grosh (1994) also documented that among all targeting methods, PMT produces the best incidence outcomes in developing countries. Multiple World Bank reports (1999, 2003) have reported the use of proxy means test for humanitarian assistance and cash transfers.

Sharif (2009) in developing a formula for PMT concluded that despite high exclusion errors in particular districts like Dhaka, the PMT model is highly progressive in its targeting performance and reasonable in its targeting accuracy.

Despite a wide variety of national and international actors employing proxy means testing for cash as well as food assistance programs, a growing body of literature warns to take caution in using the method because of the errors in the use of this technique. . Kidd et al., (2017), Kidd & Wylde (2011) make this a recurrent theme of their contribution. Identifying different sources of errors in PMT, Kidd et al. (2017) highlight not only the challenges during PMT implementation but also how infrequent surveys fail to capture the dynamic nature of household consumption leading to problems of data quality. Ravallion (2008) also takes up the issues of data and variable selection and realized that time varying measurement errors in consumption in fact make these targeting errors as 'measurement errors'.

Inbuilt exclusion errors are widely discussed in literature especially when concerning the targeting of the bottom 10% essentially because it is difficult to predict the left tail of consumption distribution with accuracy - inherent fault in methodology (Grosh & Baker, 1995). Challenges of targeting the bottom 10% as reported by Hoe (2008) in Pakistan is also consistent with the view of PMT errors in targeting the poorest. Results for the inclusion and exclusion errors in a growing number of countries show high values of these errors. Alatas et al., (2016) highlighted that as high as 93% of the poorest 5% in the conditional cash transfer program PKH were excluded. The exclusion error in Mexico's Oportunidades program was estimated to be 70% (Veras et al., 2007) while around 60% of those living in extreme poverty in Ecuador were excluded from its Bono de Desarrollo programme. World Bank (2011) released that in Cambodia, around 56 percent of poor households were excluded as an outcome of ID-poor PMT.

The Australian Aid report on assessment of PMT methodology by Kidd and Wylde (2011) assesses regression accuracy in Bangladesh, Indonesia, Rwanda and Sri Lanka and finds out that the exclusion and inclusion errors vary between 44% and 55% when 20% of the population is covered and increase even more to being between 57% and 71% when 10% is covered. This report also highlights that choosing cut-off lines based on actual poverty instead of those predicted by PMT introduces an additional coverage error. It suggests that other methods, which do not directly the poor, may be better at including intended beneficiaries. Expanding the literature on targeting gives the two possible alternatives as discussed below.

2.3.3. Community Based Targeting

Community based targeting (CBT) is when a community leader or group of community members external to the functions of the assistance program, identify the target population (Coady et al., 2004). Barrett (2002) postulates that geographic targeting can quickly, inexpensively and accurately identify needy areas within which local leaders have better information. Narbeth (2001) and Harragin (1998) also recommend engaging with traditional leadership system to ensure that the resources are distributed according to the local perceptions of vulnerability. Moreover, defining 'who is the community' is done in a range of potential actors within community based targeting, requiring different inputs. Literature suggests that depending on its specific characteristics, different local-bodies and/or preexisting community groups are likely to function differently, defining 'community' in accordance to different perspectives and purposes of the targeting program.

Although this technique has sparked the interest of international agencies particularly because of the value added of local information in the targeting process, it should be noted that it is highly context specific. Archibald & Richards (2002) took the case of Seirra Leone to show that working together with traditional leaders reinforced the grievances that had caused the civil war in the first place. Moreover, the autonomy of local leaders may fall prey to personal and social bias against particular segments of the target population depriving them from the assistance despite fulfilling the eligibility criteria. Gilligan et al. (2005) also drew to different degrees of success of the same mechanism when measuring CBT effectiveness in Bangladesh, Ethiopia and Malawi. The authors explained that CBT may work better in more resource constrained cases while highlighting that better flows of information within communities can potentially increase the targeting effectiveness.

Conning & Kevane (2002) provide a comprehensive summary of CBT by capturing the difference between the delegation and devolution within the targeting processes. They point out that the implementation and effectiveness of using community groups as target agents can be tempered by the possibility of local elite capture or preferences not being pro-poor. The authors therefore emphasize the need of carefully balanced considerations in completely relying on CBT as a targeting method.

While there is depth of literature among development agencies on other household targeting methods, there is less empirical knowledge on different forms of Community Based Targeting nor their effectiveness. The ODI report by McCord (2013) addresses this gap by their analysis on the subject. Identifying 106 social protection programs adopting CBT approaches internationally (57 in Africa, 39 in Asia, nine in Latin America and one in Europe), the study carried out a frequency analysis of overall progressivity, neutrality or regressivity[1] of the 31 programs that reported targeting performance. Two third of the programs were reported to be progressive while one third were regressive. Yusuf (2010) carried out the first large scale meta-analysis examining 30 programmes using CBT in low income countries concluding that CBT performed better in the absence of social tension, extreme wealth disparities or cultural exclusion. He found that out of the analyzed programmes, 10 programmes were progressive, 16 mildly progressive and 4 regressive.

In general, empirical literature on CBT concludes that the heterogeneity of contexts and high context sensitivity of community based targeting makes generalizing the effectiveness of this targeting technique extremely difficult. For example, studies on the PSNP in Ethiopia report both positive and negative CBT performance depending on the region under review (Samson et al., 2010). Similarly, Gomez et al (2011) report mixed results for CBT in Tanzania Social Action Fund CCT.

Since CBT differs in nature from econometric targeting methods, the set of risks this methodology faces revolves more around the risk from the actors rather the method itself. The arguments on discretion of community leaders increasing the potential of elite capture and corruption are polarizing where Coady et al., (2004**)** and Watkins (2008) support that there is a need to limit discretion whilst other studies like Nguyen & Rama (2007) pointed that community discretion led to better outcomes relative to income-based means tests. The risk of leakage and corruption is confirmed by evidence from Pakistan where local zakat comittees misdirected benefits colluding with the socially and politically influential (Arif, 2006).

Overall, the aggregation of a variety of approaches to CBT under different contexts may enable to gain more informative insights into CBT outcomes and possible success factors.

2.3.4. Self-Targeting

Self-targeting programs are defined as programs, goods or services that are open to all but are defined in a way that only the targeted will choose to participate. Barret (2002:9) accurately defines the theoretical principle of self-targeting as when ‘the cost (benefit) of participation is made an increasing (decreasing) function of one’s pre-participation income or wealth, so that only the needy find project participation attractive. The non-poor choose, of their own accord, not to use them’.

[1] Where progressivity highlights that the targeting method is pro-poor and effectively benefits the poor. Regressivity, on the other hand entails that the poor are in fact being disadvantaged as a result of targeting while in case of neutrality, the targeting technique performs no different than random allocation of the assistance.

This technique became essentially prominent in the specific food aid modality of Food For Work where the time cost of workfare is the classic example of self-targeting. To receive the assistance in terms of food or cash, participants have to do significant labor, usually in jobs involving unskilled, heavy manual labor. Another variant of self-targeting requires “volunteer” labor or time in helping organize the program in exchange of the benefit as exemplified in Peru’s soup kitchens.

Despite the substantial economic and particularly social costs of participation (high stigma attached as most of the programs are designed to be unattractive to higher-income consumers and opting for them pronounces the neediness of the participants in society), several studies, including Ravallion (1991) and von Braun (1995), support the claim that food-for-work – and self-targeting in general- effectively reach the intended beneficiaries. Lund (2002) showed how Armenian government in fact tried to encourage stigma as a self-targeting device by emphasizing that the program was specifically for the poor.

The size of transaction costs, the degree of stigma and the differences in sensitivity to them between poor and non-poor are the direct determinants of the effectiveness of self-targeting. FAO (2001) also highlighted three main elements influencing an individual’s decision to participate in a given activity, namely the costs of participation, quantity and quality of goods in the program and the social stigma of participation.

2.4. Literature Gap

In conclusion, there is not a dearth of literature on different targeting methods used in social protection programs and then adopted to cash and food assistance for humanitarian missions in crisis areas. The review of literature above attempted to trace the popularity of targeting as a concept followed by its development, not only theoretically but also as seen in empirical examples across the globe. Despite different theoretical and empirical studies highlighting the strengths and the inevitable downsides of each targeting methods, there is so far little evidence found on measuring the effectiveness of these targeting by highlighting the methodological discretion. Placing this backdrop in the context of Kenya and the OVC Cash transfer program in particular (due to reasons highlighted in the Chapter 1), it can be seen that although similar predictive exercises have been done for a variety of African countries using LSMS surveys, evaluations on Kenya are rare due to unavailability of LSMS data. Moreover, the PMT simulations found on Kenya use KIHBS data from 2005/06 while this study aims to not only add to, but update the results using the latest data from 2015/16.

Chapter 3. The Context of Kenya

This chapter puts the targeting literature above in the context of Kenya and in particular for the Cash Transfer for Orphans and Vulnerable Children (OVC). Divided in two subsections, the first section gives an overview of the program chosen as case study for simulation, along with the targeting methods currently employed and concludes with the Program's shortcomings.

3.1. Description of OVC-Cash Transfer and The Employed Targeting

Forming about 19 million out of 34million population of the country (Statistics, 2010), the child population in Kenya became an increasingly significant vulnerable group especially after the HIV/AIDS pandemic in the country that caused many children loosing either or both of their parents. In response to the crisis, discussions to target and protect vulnerable children gained grounds in the course of parliamentary elections of 2002. Consequently, Government of Kenya has put in place a National Policy and National Plan of Action for Orphans and Vulnerable Children (OVCs).

Beginning in 2004 and still on-going, OVC-CT is one of the four major cash transfer programs currently operating in Kenya under a harmonized program of National Safety Net Programme consisting of:

i) Cash Transfer for Orphan and Vulnerable Children
ii) Older Persons Cash Transfer
iii) Cash Transfer for People with Severe Disability
iv) Hunger Safety Net Programme

To date, all of these four programs employ consumption expenditure-based PMTs as a pivotal step in one of the several levels of identification of beneficiaries. However, acting independently of each other in the delivery of transfers, each of these programs implements a proxy means test using different concepts of poverty (Villa, 2016).

According to the several stages of targeting as per the Programme's Operation Manual, it can be drawn that the targeting process essentially comprised of two-stage targeting employing CBT in the first step followed by a Proxy Means Test.

Since the main objective of the program is to: "Provide a social protection system through regular and predictable cash transfers to families living with OVCs in order to encourage fostering and retention of OVCs within their families and communities, and to promote their human capital development" (Ward et al, 2010: 01), the broad target population was therefore defined as households containing at least one OVC where a child (under 18 years of age) is defined OVC as being orphaned (single – with one parent dead, or double- with both parents dead), being chronically ill[2], being taken care of by a chronically ill

[2] Among the illnesses under the category of chronic illness are: Tuberculosis, HIV/AIDS or Cancer (Hurrell et al., 2008).

person or living in a child headed household. In the first stage, CBT is employed to ascertain the OVC status as collected and confirmed by Local OVC Committee (LOC) who visit households and record data on their characteristics to determine potential eligibility. A list of identified households is then generated as the Record of Identified Households if the household has at least one OVC, is poor (as per local self-defined poverty criteria) and if is not a beneficiary of any other transfer programs. After further verification by revisits and detailed questionnaire, this list of potentially eligible OVC households is then run by a poverty test to be classified as poor or non-poor.

At the initiation of the program, a multidimensional poverty indication (MDI) would be carried out using 17 of the criteria listed in Table 2.

Table 2.

Criteria for multi-dimensional poverty indication used in OVC Cash Transfer targeting

1)	None of the adults in the household reached standard 8;
2)	Caregiver is not currently working or s/he is working and is none or 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-dun
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)	No real state property here or elsewhere;
12)	Two or less traditional zebu cattle;
13)	No hybrid cattle;
14)	Five or less goats;
15)	Five or less sheep;
16)	No pigs;
17)	No camels.

Note. Adapted from OPM Baseline Evaluation Report by Hurrell et al.,(2008)

Households exhibiting 8 out of these 17 characteristics were identified as eligible. An initial amendment was made in the system by UNICEF ESARO in 2008 when the eligibility criterion was raised to households exhibiting 10 instead of 8 of the above characteristics. However, the baseline evaluation report raised concerns that this poverty test was ineffective in directing resources at the poorest and that at the time of the baseline survey, only one quarter of the poorest OVC households were selected to be included in the program (Hurrell et al., 2008). As a result of such high exclusion, this step of the targeting process was revised to developing and using a more sophisticated approach of proxy means test using the data available from KIHBS 2005/06. While the initial approach gave equal weight to all characteristics, differential weights were given using a PMT model.

Further evaluation in 2010 **(**Ward et al**.**,2010) however, emphasized that although the Programme was successful in enrolling its target population of OVCs with low leakage, it is still not effective in differentiating and identifying poor households as a poor OVC household only has a modestly better chance to be included in the program than an 'average' OVC. As a result, this poses a serious equity risk because many of the poorest OVC households are excluded and those better off receive support from the program. Therefore, the poverty test of OVC-CT Kenya is the primary area of attention of the sections that follow in this thesis.

3.2. Limitations of the Programme's Model

In recent years, increasing concerns have been raised about the conceptual framework of defining child vulnerability. Assessments by WFP (2018), as well as the program's evaluation by Oxford Policy Management both draw on the fact that the common perception of children identified as OVC being necessarily vulnerable is an untested claim. Through multivariate analysis, WFP reiterates that orphaned children are not more likely to live in poverty when in fact, the share of non-orphans and double orphans living below the poverty line was identical when calculated based on HSNP-OPM Panel Household Survey(Silva-Leander, S. & Merttens, F., 2016). Moreover, these results are not unique to Kenya as other studies (UNICEF, 2014a; Akwara, 2010; Mishra et al., 2008) also found out that in other African countries that orphans are not necessarily more disadvantaged than their non-orphaned peers. This is also consistent with the comparison across a range of non-income based indicators, made in the Programme evaluation (Ward et al., 2010**)** between the national population (based on DHS) and the study population. The authors conclude that the study population of OVC households is only mildly worse off than the national population as a whole and no worse than the national rural population.

Moreover, the detailed analysis on child vulnerability and cash transfer net in Kenya by WFP and UNICEF (Gelders, 2016) also draws that while indicators like living with adults who lack education or living with anyone other than child's parents can be relevant indicators but these characteristics are far less reliable predictors of childhood vulnerability than household wealth, which is the only reliable and consistent indicator to define vulnerability.

Another area highlighted in program evaluations is the bias of the program against children under 5 primarily again due to the criteria used to define eligible households. It is shown that the share of children becoming single or double orphans increases from around 3% for under-five to almost 19% for the children aged 15-17 years (KNBS, 2015). As a result, older children are , by default, more likely to fulfill the eligibility criteria and hence are more likely to be selected as beneficiaries of the program.

Although the main objective of the program was not aimed at addressing poverty but to encourage households to foster and take care of vulnerable children and orphans so as to develop their human capital, the Programme was posed with the inevitable choice to prioritize support for poor OVC households. Therefore, instead of targeting well-off orphans, including poor non-orphans makes a strong argument for a design reorientation to retain the focus on poverty as the core objective of the program.

Chapter 4. Data and Methodology

This chapter explains the data and empirical methodology employed in the study. The first subsection describes the Kenyan Integrated Household Budget Survey (KIHBS) 2015/16 as the dataset used and refined for the study in detail. This is then followed by econometric specification of the proposed PMT model, along with expanding on the descriptive statistics of the sample population.

4.1. Data: KIHBS Survey and some descriptive statistics of the population

4.1.1. Data Set

KIHBS 2015/16 is the second integrated Household Budget Survey (HBS) in Kenya and the first one of the kind carried out under the devolved system of government. The first HBS was Rural Household Budget Survey conducted in 1981/82, followed by Urban Household Budgets of 1983/84 and 1993/94. Kenyan Bureau of Statistics then undertook a series of Welfare Monitoring Surveys after which the first Integrated Household Budget was conducted in 2005/06. The survey collected data on multiple indicators from consumption expenditure to household characteristics, housing conditions, education, general health conditions, household income and credit, transfers, information and communication technology, domestic tourism, justice as well as shocks to household welfare using information on household and individual level.

The sampling frame used in the survey is the fifth National Sample Survey and Evaluation Program (NASSEP V) master frame developed from Population and Housing Census in 2009. The 2009 census administratively divides Kenya into 47 counties, subdivided into districts, districts to divisions, divisions to locations and finally to sub-locations. The survey therefore has the geographical coverage of all counties. From this master frame, stratified sample was selected for KIHBS 2015/16, dividing each county into rural and urban areas, resulting in 92 sampling strata. From each of these sampling stratum, samples were selected by a two stage selection procedure. In the first stage, primary sampling unit of selection of households was made in the form of 2388 clusters with equal probability. 10 households from each of these clusters were then selected at random comprising a total of 23880 households as the national sample size for KIHBS 15/16. Furthermore, since the sample allocation was not proportional to the size of the strata and hence the survey data was not self-weighting, these households were weighted based on selection probabilities in each domain. This adjustment makes the survey data to be representative not only at the national but also on the county level.

Out of these sampled households, 91.3% (21773 households) participated and completed questionnaires. KIHBS 2015/2016 had employed a set of seven survey instruments which included three main questionnaires, two diaries, one market questionnaire and one community questionnaire. This dissertation makes use of the three main questionnaires briefly described hereunder.

i) The household members' information questionnaire – this module collected information on demographics, education, health, labor, child health, ICT services and domestic tourism on an individual level;

ii) The household level information questionnaire – this module collected information including the household characteristics of housing, water, sanitation, household economic enterprises, income and credit as well as shocks to household welfare, justice and ICT at household level;

iii) Household consumption expenditure information questionnaire**-** this section included all information on a household's purchases and consumption of food, nonfood and services.

As described in the following sections, while the first two questionnaires helped extract information on explanatory variables in this dissertation, the module on consumption expenditure is used to derive the main dependent variable used in the analysis.

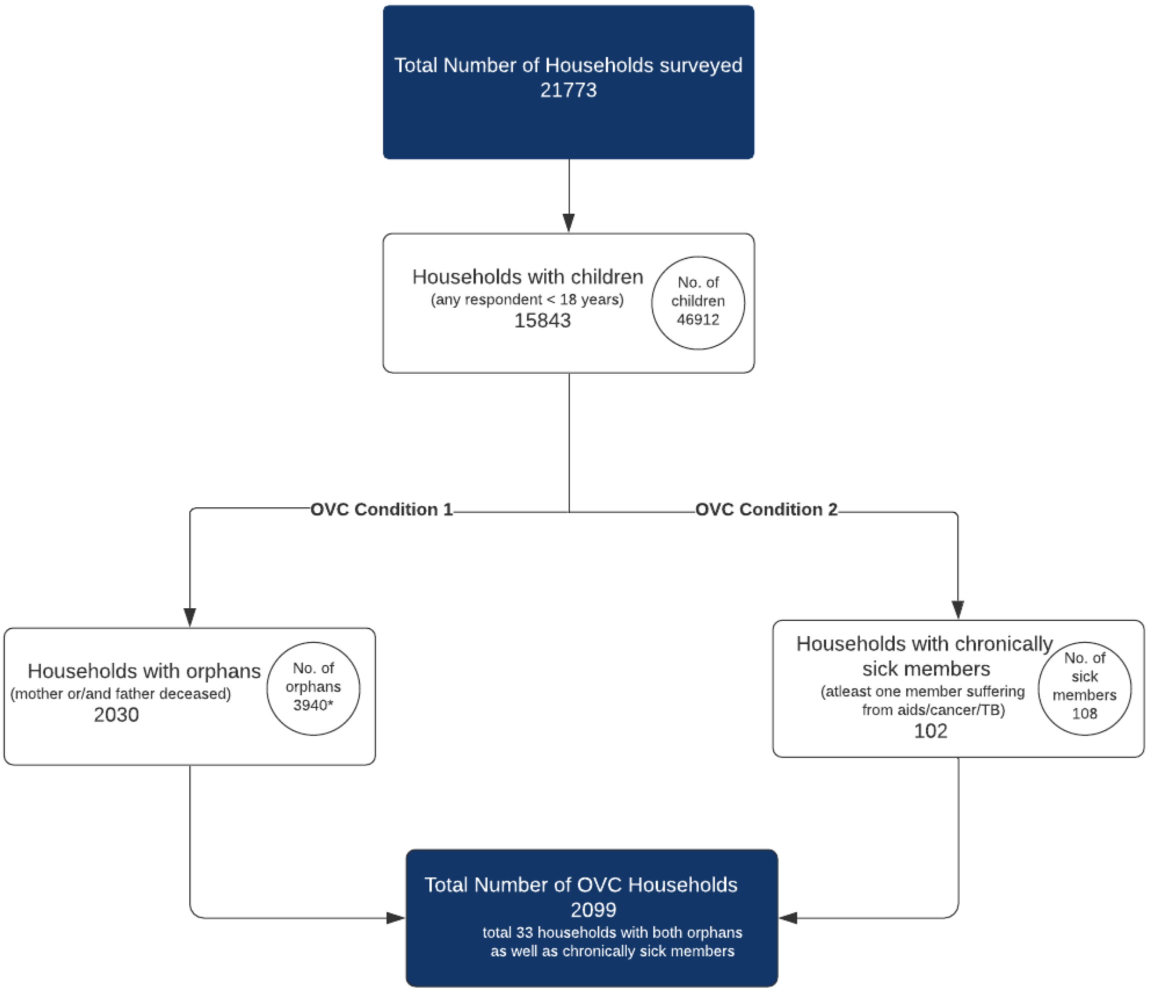
4.1.2. Data Description

In order to extract data on consumption and the proxy indicators to be used to predict household consumption, the data sample is first generated as per the broad target population of the program i.e. the OVC households. As discussed in detail in Chapter 3, using the criteria employed by Oxford Policy Management **(**Hurrell et al., 2008**)** for the identification of OVC households, these households are defined as those with orphan children[3] or those with children taken care of by chronically sick household members.

[3] The calculation of 3940/46912 children as orphan in this study confirms the percentage of orphans provided by KNBS 15/16.

Figure 1.

Calculation of OVC Households using KIHB 2015/16



Note. Author's elaboration

A dataset comprising of 2099 households is obtained by merging households meeting either of the two criteria above, as shown in Figure 1 for the subsequent analysis that follows in the next chapter.

Figure 1 reveals that the presence of orphan children is the single most important determinant of identifying the target population of this program. Further, with 51% (2014) males and 49% (1926) females when caluclated using KIHBS 2015/16, there exists an almost equal gender ratio among the orphan children. Moreover, when analyzed according to age,it can be seen in Table 3 that the largest proportion of vulnerable target population (i.e. orphans) lies between 10 and 15 years of age, giving a mean age of 11.5 years. [4]

Table 3.

Age distribution of orphans – number of orphans in each age group

Age (years)	**Number of Orphan Children**
Under 5	290
5 ≤ Age < 10	878
10 ≤ Age < 15	1564
15 ≤ Age < 18	1208

Note. Author’s calculations using KIHBS 2015/16.

Similarly, an analysis of the OVC households defined by atleast one child and one chronically sick adult shows that among the three illness defined as chronic in the targeting Manual of OVC, AIDS has the highest incidence of 48% while TB and Cancer are the illnesses reported by 32% and 20% of chronically ill, respectively. These results are expected due to the AIDS pandemic in Kenya in the late 80s. The mean age of 108 individuals suffering from either of these three diseases is 40.7 years.[5]

4.2 Econometric Specification of Proxy Means Test Model

This section aims to expand on the econometric computation of Proxy Means Testing.

4.2.1. PMT model and descriptive statistics of sample population

When formal income data (through income slips, tax returns) are not available, observable and easy to verify characteristics are used to estimate a household’s income or consumption. By using actual quantifiable data often available from household surveys, a PMT model identifies a set of household characteristics that correlate significantly with the income/consumption. These variables are then used to predict a household’s welfare using different econometric techniques, hence acting as proxies for actual welfare. These predictions are henceforth used in identifying households or individuals that classify as eligible or non-eligible for any cash or food assistance when measured against set cut-offs/eligibility criteria specific to each program. While implementation and delivery also form an equally important part in determining a PMT’s effectiveness, this study assesses the method’s effectiveness depending on the predictive power of a PMT model to correctly identify households who actually fulfill the eligibility criteria as eligible while correctly excluding those who lie above the eligibility threshold.

This correspondence between welfare and welfare indicators is drawn using KIHBS 2015/16 that contains data on both consumption aggregate and household characteristics as described in section 4.1.1. For the

[4] Based on author’s calculation using KIHBS 2015/16
[5] Based on author’s calculation using KIHBS 2015/16

purpose of the predictive simulation of the PMT in this dissertation, a series of step by step regressions are carried out with each of the broad categories of explanatory variables described in the section below, added at each stage to calculate a "score" for one household. These scores are derived from Ordinary Least Square(OLS) regressions of (log of) monthly per adult equivalent total consumption expenditure (deflated) on the variables shown in Table 4 below.

Table 4.

Variables used and their construction

	Variables	**Construction**
Dependent Variable	Household Welfare	Monthly total consumption expenditure per adult equivalent (deflated) Logarithmic Transformation applied to give log of monthly total consumption expenditure per adult equivalent (deflated)
Independent Variables		
Location Variables	Place of residence – Rural Urban proximity	Is the place of residence urban: Dichotomous Variable 1: Yes; 0: No
Household Characteristics	Household head-Age	Continuous variable
	Household head-Gender	Is the household head male: Dichotomous variable 1: Yes ; 0: No
	Household head-Highest level of education	Highest level of education of household head Categorical variable 0: None; 1: Pre-Primary, Primary, Madarsa; 2: Post Primary, Secondary, University Undergrad, University Postgrad
	Employment engagement of Household Head	If HHhead has worked on own account or as employer on a farm owned or rented in the last 7 days If HHhead has worked as an employee for wage, salary, commission in the last 7 days If HHhead has worked on own account of employer in a business in the last 7 days For all the above: Dichotomous variable

		1: Yes ; 0: No
	Household size	Is the household size less than 5 Dichotomous variable 1: Yes ; 0: No
	Density of people	Number of people per room Continuous variable generated by dividing the total number of habitable rooms by household size
	Number of Orphans	Is the number of orphans in a household greater than 1 Dichotomous variable 1: Yes ; 0: No
Additional Assets	Access to Additional Assets	Access to • Television • Mobile Phone • Laptop/PC/Tablet • Internet Dichotomous Variable 1: Yes; 0: No
House Characteristics	Ownership of dwelling	If the household owns the dwelling: Dichotomous Variable 1: Yes; 0: No
	Material of walls	Dichotomous Variable 0: No Walls/Conventional walls of mud/grass/bamboo; 1: Walls of cement/brick/corrugated iron
	Material of floor	What is the floor made of Categoric Variable 0: Earth/Sand; 1:Dung/Bamboo; 2: Wood/Tiles/Cement/Carpet
	Material of roof	What is the roof made of Categoric Variable 0: Grass/Makuti; 1:Dung; 2:Corrugated Iron/Concrete/Tiles
	Toilet Facility	What sort of toilet facility does the household use Categoric Variable 0: No facility/Bucket; 1:Flushed to piped server/septic tank/pit; 2:Latrine (with or without slab)
	Drinking water source for the past 12 months	Is the source of water unit outside the living facility(not piped into dwelling/plot) Dichotomous Variable 1: Yes; 0:No
		Is the main source of energy used for cooking other than firewood

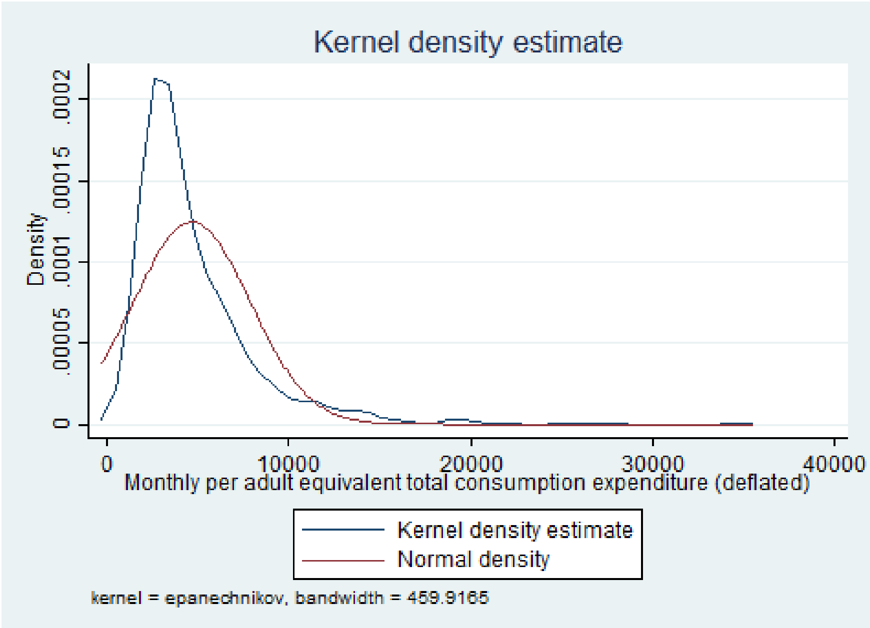
Main source of energy for cooking	Dichotomous Variable 1: Yes; 0:No
Main source of energy for lighting	What is the main source of energy for lighting Categoric Variable 0: Fuel-wood/candles; 1:Electricity from Mains; 2:Generator/Solar Energy; 3:Parrafin Lamps(Lantern/Tin/Pressure)
Main cooking appliance	Does the household use cooking appliance other than traditional fire stone Dichotomous Variable 1:Yes; 0:No
Floor-Roof Interaction	Interaction variable combining the floor and roof material

Literature on choosing a proxy for welfare suggests that expenditure is generally presumed to be a better measure than income. Reasons for this include that households are less likely to under-report their consumption behavior as opposed to the risk associated with intentionally reporting incorrect low incomes in order to avoid taxation or other negative repercussions. Moreover, consumption expenditure also does a better job in capturing the households operating on a larger share of in-kind income than those that do not. Furthermore, since expenditure varies less than income over time, it helps draw comparisons between households with regular incomes with those with seasonal or sporadic sources of income (Grosh & Baker, 1995**).**

Based on this, the monthly per adult equivalent total consumption expenditure (deflated) as available in the KIHBS 2015/16 for each household is taken as the dependent variable. The Kernel distribution of this is represented in the Figure 2.

Figure 2.

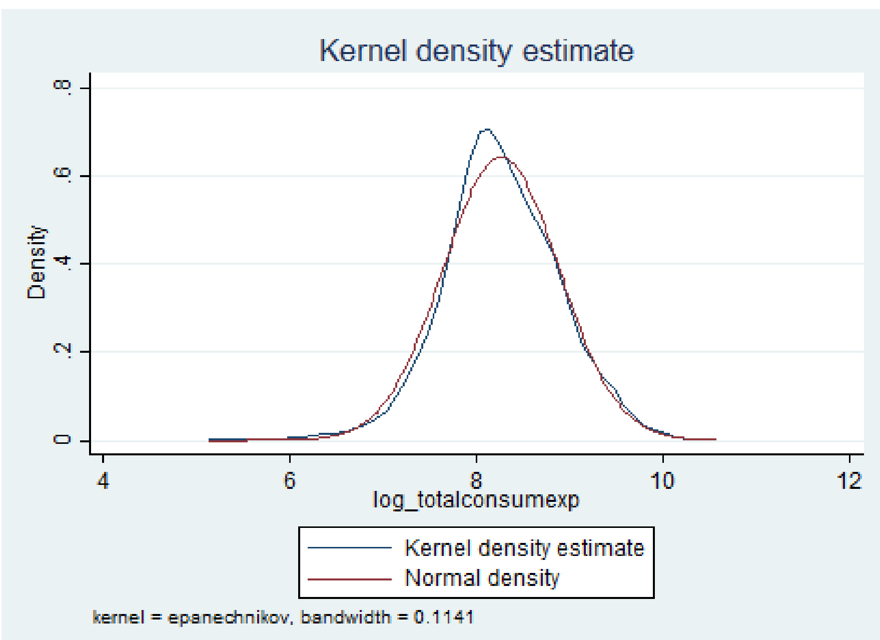
Kernel distribution of monthly total consumption per adult equivalent (deflated)



To reduce the high rightward skewness of this variable, a logarithmic transformation is applied which yields the result in Figure 3 showing that the transformation indeed normalizes the distribution of monthly per adult equivalent total consumption expenditure.

Figure 3.

Kernel distribution of log of monthly total consumption expenditure per adult equivalent (deflated)



The regressors, as shown in Table 4 are grouped into four broad categories namely location, house characteristics, access to additional assets and house characteristics. These variables are selected based on the proxy means tests applied in Cameroon, Ghana, Kenya, Malawi, Mozambique and Senegal in a comprehensive study on Safety Nets in Africa by The World Bank (Carlo del Ninno and Bradford Mills, 2015). Outside Africa, PMT models developed in South Asia have also used a similar broad categorization of the indicators with the variation of household assets included in the models by Hou(2008), Narayan et al(2002) and Sharif(2009) for Pakistan, Sri Lanka and Bangladesh, respectively.

For a flexible form of regression and for statistical significance of theoretically significant variables, most continuous variables are converted to dichotomous variables and variables with numerous categories are classified into reduced categories on the account of not the theory but also according to the distribution of observations in each of those categories. Multiple iterations are then carried out with different subsets of these variables to define the above described categorizations and after checking for possible multicollinearity, the final set is included in the step by step regressions.

The descriptive statistics of these variables are presented in Table 5 which, along with the distribution in the entire sample, represents means of these indicators in rural and urban OVC households separately.

Table 5.

Summary Statistics for independent variables used in the regression

	Rural Households	Urban Households	Total Sample	S.D
Total monthly consumption expenditure, per adult equivalent (deflated)	4085.36	5999.31	4712.06	3200.46
Household Characteristics				
Male Head	0.38	0.39	0.38	0.48
Age of Head	50.11	47.19	49.16	15.3
Head has no education	0.30	0.23	0.27	0.45
Head has pre-primary/primary/madarsa education	0.49	0.44	0.47	0.50
Head has post primary/secondary/university education	0.21	0.33	0.25	0.43
Head worked for wage in the last 7 days	0.20	0.32	0.24	.4309
Head worked in an enterprise or business (barber, shopkeeper etc)	0.18	0.31	0.22	0.41
Head worked in own or rented far	0.58	0.33	0.50	0.50
Household size is less than 5	0.55	0.55	0.55	0.49
Number of people per room in the household	2.92	2.91	2.92	1.98
Household has more than one orphans	0.49	0.47	0.48	0.50

Household Assets				
Television	0.09	0.34	0.17	0.38
Computer/Laptop/Tablet	0.02	0.06	0.03	0.17
Mobile Phone	0.73	0.86	0.77	0.42
Internet	0.14	0.25	0.18	0.38
Own house	0.94	0.67	0.85	0.36
House Characteristics				
Wall: No Walls/Conventional walls of mud/grass/bamboo	0.69	0.39	0.59	0.49
Wall: Cement/Brick/Corrugated Iron	0.31	0.61	0.41	0.49
Floor: Earth/Sand	0.48	0.24	0.40	0.49
Floor: Dung/Bamboo	0.27	0.13	0.22	0.41
Floor: Wood/Tiles/Cement/Carpet	0.25	0.62	0.37	0.48
Roof: Grass/Makuti	0.19	0.06	0.14	0.35
Roof: Dung	0.01	0.003	0.01	0.10
Roof: Corrugated Iron/Concrete/Tiles	0.79	0.93	0.84	0.36
Toilet: No facility/Bucket;	0.22	0.08	0.18	0.38
Toilet: Flushed to piped server/septic tank/pit	0.02	0.16	0.06	0.24
Toilet: Latrine (with or without slab)	0.76	0.76	0.76	0.43
Drinking water unit is outside the dwelling	0.90	0.71	0.84	0.36
Main energy source for lighting: Fuel-wood/candles	0.04	0.01	0.04	0.18
Main energy source for lighting: Electricity from Mains	0.09	0.42	0.19	0.39
Main energy source for lighting: Generator/Solar Energy	0.22	0.13	0.20	0.39
Main energy source for lighting: Parrafin Lamps(Lantern/Tin/Pressure	0.64	0.43	0.57	0.49
Main energy source for cooking is (other than) firewood	0.07	0.46	0.20	0.40
Main cooking appliance is (other than) traditional firestone	0.18	0.52	0.30	0.46

Note. Author's elaboration using KIHBS 2015/16

Some key observations for the characteristics of OVC households and the summary statistics presented above are discussed hereunder.

Location Variable: The location variable captures the effect of rural and urban proximity of the households used in the analysis. This variable is important to analyze and improve the coverage of safety net programs because of the insight it can give in assessing poverty incidence by place of residence.

Author’s calculations show that with a total of 1331 out of 1979 OVC households identified as rural, the sample population has a much larger share of rural than urban households. Although from a theoretical standpoint, it may be ideal to use different PMT models for rural and urban areas to capture structural differences, this research draws from the PMT iterations carried by Cnobloch and Subbarao(2012) and Sharif(2009) to use a single model not only because of substantial reduction in sample size without significant improvement in results when run separately, but also because of the ambiguity of distinction between rural, peri-urban and urban areas in some parts of Kenya. This study, however, dissects the location variable in detail in the analysis section and presents an iteration of the basic PMT applied to rural households discussed in detail in Section 5.4.2.

Frequency of OVC households by counties shows that 5 counties with the highest number of OVC households are Migori (127), Siaga (95), HomaBay (95), Kakamega (73) and Kisumu(70) while Nairobi contains the lowest number of 19 OVC vulnerable households included in the regression.

Household demographics: This set of variables captures the demographic conditions of OVC households mainly drawing from Nguetse-Tegoum and Stoeffler (2012**)**’s study on Cameroon and uses household head’s age, education and employment following the literature.

A greater number of vulnerable households can be seen to be headed by female household heads (1230 out of 1978 OVC households). While Table 5 shows the mean age of household heads to be 49 years of age, the sample had a household head as young as 13 years with the oldest household head being 95 years of age.

The highest level of education of household head is captured by dividing the response to three main categories described in Table 4. Unsurprisingly, it is observed that while the highest mean share is of household heads having pre-primary education, around as many as 11% of urban households have more household heads with post primary, secondary and higher secondary education than OVC households located in rural areas.

The employment of head of household is captured by their engagement in the kind of employment activity in the last 7 days. 50% (984) households reported to have household heads who worked on their own account or as an employer on a farm owned or rented for cultivating crops or maintaining livestock. As expected, this share is significantly higher in rural(58%) than that reported in urban households (33%). Almost an equal proportion of household heads reported to have been engaged in wage employment or business enterprise with frequencies of 24% and 22%, respectively.

The household size variable is transformed from continuous to binary with a cut off at the mean household size of OVC households used in the analysis as calculated to be that of 5.5 people. The mean density in these households is 2.9 people per habitable room with maximum extending up to 12 people per room.

Access to additional assets: Access to assets like TV, mobile phone, internet and computer has been added in the model to test for the correlation with poverty and access to information by these vulnerable households. Ownership of these by OVC households highlights that mobile phone is the most popularly accessed among the chosen additional assets with 1526 households having mobile phones. Some studies like Sharif(2009) drop the assets like mobile phones which are, although correlated with poverty, but are subject to rapid changes in access from the time of survey data used. Due to the advantage of recent KIHBS, this study is able to retain them. While a very low number of households reported to have access to Computer/Tablet(61), almost an equal proportion had access to television(342) and some sort of internet(357).

House Characteristics: This set of variables is popularly used as indicator of welfare because of the ease of verifying them, and have been included in OVC targeting ever since the initiation of the program, in both MDI and PMT approach as shown in Table 2 in Section 3. This study, therefore, retains them in the PMT simulation.

While the basic ground of transformation of these variables is essentially to distinguish between conventional and improved facilities to target the most vulnerable, categories are retained for roof and floor material as well as for source of light and toilet facility due to greater variety of responses as well as due to difficulty in classifying them as conventional and unconventional. Following one of the two major reasons, these variables are transformed to those in Table 4: i) the independence of categories within each variable[6] to fulfill the implicit assumption that categories are identically and independent distributed for unbiased regression results; ii) the categories are balanced with a relatively similar proportion of observations in each category to avoid problems with sample inadequacy. Due to a rather clear differentiation between categories, the material of wall and source of energy as binary variable gave better results for predicting household poverty in the model. These are, therefore, transformed and retained as binary with none or conventional walls[7] grouped together as the reference category for wall material while setting firewood weighed as reference against all other sources for the source of energy for cooking. Among the easily observable housing materials, 59% of all OVC households have walls built of either mud or mud with bamboo. Corrugated iron sheets are the single most commonly used roof material within these households with grass/thatch roofs being the second to follow, having a much smaller percentage share of 15% households using them. While the greatest majority of households have no flooring (i.e. earth/sand), a significant percentage (37%) in fact has cement floors, making cement the second most frequently observed floor material among OVC households.

[6] For example, the response categories of mud and mud&bamboo are grouped together as one. (See Appendix for statistics per disaggregated categories)

[7] Walls made of Cane/Grass/Mud/Bamboo with Mud/Stone with Mud/Uncovered adobe

Most OVC households use the toilet facility of a pit latrine. Combing the shares of pit latrines with and without slab gives the majority of 76% households using this facility while 18% do not have any proper sanitation facility and use buckets or fields/bush for their needs. Moreover, among households with any kind of toilet facility, 45% share this facility with other households.

Moreover, a small percentage of 16% households have access to a water unit inside i.e. piped inside the dwelling or in the yard. Not surprising is the fact that when tabulated against location, 72% of households having to access water from any source outside (such as combined tap, dug wells, water from spring) are rural households. However, the dissection analysis of urban households shows that even in the urban areas, majority (55%) of OVC households use water source other than piped water. Similar percentages are obtained when main source of water for domestic uses is analyzed but due to multicollinearity, the latter is not included in the model.

The detailed shares of households with disaggregated, original categories are presented in the Appendix.

Finally, an interaction term for floor and roof material is added in the model amongst interactions within all three variables of roof, wall and floor for better estimation.

The respective OLS regression coefficient of each of these variables acts as their weight in the calculation of the PMT score of each household which is, henceforth, predicted as:

$\theta_i = \beta_o + \beta_1 \textit{Location} + \beta_2 \textit{ Household Characteristics} + \beta_3 \textit{Access to Additional Assets} + \beta_4 \textit{House Characteristics} + U_i$.

where:

θ_i = Log of monthly adult equivalent total consumption spending (deflated); and each subgroup of independent variables as described in the table above.

Once the aggregate score of each household is calculated, the predicted expenditure or welfare reflects that lower the score, the poorer is the household.

4.2.2. Cut off Lines, Eligibility and Errors of Inclusion and Exclusion

Once the PMT score is calculated, the eligibility of households is determined against set cut-offs. These thresholds are set at different poverty cut-offs using percentiles of actual consumption expenditure, ranging from 5th to 40th percentile, depending on the part of population that a transfer program aims to target. Majority of studies referred in the review of literature on PMT run simulations of the predictive capacity of a PMT model using different thresholds.

A household is classified as poor and hence eligible for the transfer if its predicted welfare (PMT score) falls below the threshold, also known as the targeting line. Choosing this cut off line is also crucial in determining the level of targeting errors because the performance of PMT varies according to where the threshold is set. Since the exercise is based on predicted welfare instead of actual, it is expected that some poor will always be incorrectly identified as non-poor while a certain percentage of non-poor will be predicted as poor by the model. This essentially means that the predicted and the actual consumption levels fall on two different sides of the eligibility criteria. When the actual consumption is below and the predicted score is above the cut-off, the model suffers from an Error of Exclusion. “Under-coverage” is then obtained by dividing the error of exclusion by total number of actually poor households. Errors of exclusion are more severe when in case of food transfers or emergency aid because of the acute impact on those in need but deprived due to incorrect targeting.

On the other hand, budgetary losses occur when those not actually needing the benefits are identified as eligible in the program on the basis of the predicted consumption falling below the cut off while the true consumption level lies above. This error is referred to as ‘Error of Inclusion’ and the percentage of benefits received by those ineligible is called “Leakage”. Table 6 explains the computation of these errors.

Table 6.

Computation of Inclusion and Exclusion Errors

	Target Group – “Actual Poor” (actual welfare ≤ cut-off)	Non-Target Group – “Actual Non-Poor” (actual welfare > cut-off)	Total
Beneficiary – “PMT Poor” (predicted welfare ≤ cut-off)	Targeting Success (S1)	Inclusion Errors (F1)	P1
Non-Beneficiary – “PMT Non-Poor” (predicted welfare > cut-off)	Exclusion Errors (F2)	Targeting Success (S2)	P2
	A1	A2	

Leakage = F1/P1	Under-coverage = F2/A1

Note. Adapted from Huo (2008).

The trade-off between these two errors is a policy matter decided by the aim of the program. While most studies commissioned by the World Bank use ‘actual’ consumption levels as the cut-off lines, Kidd and Wylde (2011:2) highlight in a report that by doing so introduces an additional error of ‘coverage’. By definition, errors of inclusion and exclusion should be symmetrical by “*assuming that the eligible population corresponds to the coverage of the program*”. The authors explain it as “*For example, in a program targeted at the poorest 10%, if 40% of those eligible are excluded then the other 40% included must not have been eligible (that is, they are not among the 10% poorest), making both exclusion and inclusion errors 40%”.* (Kidd and Wylde (2011:2)

Brown & Ravallion (2016), in this case, refers to these symmetrical errors simply as the “Targeting Error Rate” explaining the intuition that every time an actual poor is excluded as being predicted as non-poor by the PMT, it has to be replaced by an inclusion error of including a household that is in fact an actual non-poor, to keep the count of poor constant. However, the assumption of program size being equal to the target population is not met when actual consumption levels are chosen as cut off. The report highlights that this approach has two key problems:

i) Simulating the targeting efficiency in terms of actual consumption questions the relevance of PMT in the household survey data as the basic reason of employing a proxy means test is when complete information on consumption is not available.

ii) The additional coverage error mixes the analysis of the inclusion and exclusion error making it difficult to differentiate if the exclusion error is attributed to the failure of the PMT formula to predict consumption or is related to coverage that is lower than targeted.

While mechanically, setting cut-offs based on predicted consumption-expenditure may seem more relevant and makes interpretation of inclusion and exclusion errors more straightforward, it is a rather strong assumption because more often than not, the target population does not exactly equal the program coverage. Regardless of which cutoffs are used, the difference in using predicted and actual consumption is important to understand the targeting efficiency of a PMT model. These differences – the gap between 'coverage' and 'coverage error'- reduce as the target population size increases.

Therefore, this dissertation considers both of these options on the simulated PMT and draws on how the predictive power responds to cut-offs chosen with different theoretical reasoning.

4.3. Limitations of Using OLS in This Model

Although very popularly used in previous studies of PMT simulations, econometrically speaking, OLS may not be the most appropriate technique for predicting poverty primarily because minimization of squared errors between actual and predicted welfare of households is a different theoretical problem than that of poverty minimization. Grosh and Baker(1995) compare four algorithms and establish that while Ravallion and Chao(1989)'s algorithm directly minimizes poverty, the method is cumbersome to use when a large number of predictive variables are available. On the other hand, when using OLS, PMT calculations may suffer from the risk of endogeniety as the decisions of households about the explanatory variables are not fully independent of the decisions that determine welfare (the dependent variable of OLS). However, since the focus of the targeting simulation in this thesis is to correctly identify poor, and not to explain why they are poor, the easily computable method of OLS is assumed as sufficient.

Chapter 5. Results and Analysis

5.1. Regression Results and predicted consumption

After several iterations on inclusion of different variables listed and described above, this dissertation presents the results of the step by step regressions, following the addition of variables as per the four broad categories of regressors. Step by Step regressions help gauge the significance of each set of variables in explaining a household's welfare by the incremental contribution of each set of variables to the R-square as shown in Table 7**.**

Table 7.

Regression Results

	Model 1	**Model 2**	**Model 3**	**Model 4**
Location: Urban	0.417*** (0.039)	0.349*** (0.035)	0.245*** (0.035)	0.124*** (0.033)
Household Characteristics				
HHhead gender : male		0.027 (0.032)	0.021 (0.030)	0.027 (0.029)
HHhead education: no education *omitted*				
HHhead education: pre-primary and primary		0.154*** (0.040)	0.075** (0.038)	0.033 (0.037)
HHhead education: post primary and above		0.389*** (0.047)	0.224*** (0.046)	0.139* (0.046)
HHhead employment: wage		0.076** (0.039)	0.027 (0.036)	-0.003 (0.034)
HHhead employment: business enterprise		0.167*** (0.045)	0.131*** (0.039)	0.100** (0.037)
HHhead employment: own or rented farm		0.020 (0.032)	0.042 (0.031)	0.066* (0.029)
HHhead age		-0.002* (0.001)	-0.001 (0.001)	-0.001 (0.001)
Household size: less than five		0.115*** (0.032)	0.173*** (0.030)	0.156*** (0.030)
Number of people per room		-0.082*** (0.010)	-0.062*** (0.009)	-0.058*** (0.009)
Number of orphans in house: greater than one		-0.104*** (0.030)	-0.080*** (0.028)	-0.089*** (0.026)
Access to additional assets				
Television : yes			0.254*** (0.045)	0.097* (0.051)
Computer: yes			0.309*** (0.074)	0.270*** (0.072)
Mobile Phone: yes			0.258*** (0.038)	0.172*** (0.038)
Internet: yes			0.098* (0.042)	0.053 (0.041)
House Characteristics				

Own house: yes	0.023 (0.052)
Walls: cement/brick/corrugated iron	0.122*** (0.035)
Floor: No floor/Earth/Sand *omitted*	
Floor: Dung/Bamboo	0.214* (0.095)
Floor: Wood/Tiles/Cement/Carpet	0.115 (0.081)
Roof: Grass/Makuti *omitted*	
Roof: Dung	0.133 (0.165)
Roof: Corrugated Iron/Concrete/Tiles	0.087 (0.065)
Toilet Facility: no facility/bucket *omitted*	
Toilet Facility: flushed to piped server/septic tank/pit	0.233*** (0.087)
Toilet Facility: latrine (with or without slab)	0.012 (0.046)
Drinking water unit: outside the living facility	-0.011 (0.046)
Main source of energy for cooking: other than firewood	0.108** (0.054)
Main source of energy for lighting: fuel-wood/candles *omitted*	
Main source of energy for lighting: Electricity from mains	0.447*** (0.165)
Main source of energy for lighting: Generator/Solar Energy	0.423*** (0.154)
Main source of energy for lighting: Parrafin Lamps(Lantern/Tin/Pressure)	0.362** (0.146)
Main cooking appliance: other than traditional firestone	0.118*** (0.041)
Floor-Roof Interaction	
Dung Floor* Dung Roof	-0.060 (0.191)
Dung Floor*Iron/Concrete/Tile Roof	-0.262** (0.104)
Cement/Tile Floor* Dung Roof	0 (empty)
Cement/Tile Floor *	-0.153*

Iron/Concrete/Tile Roof				(0.087)
Constant	8.206***	8.267***	7.981***	7.547***
	(0.018)	(0.096)	(0.096)	(0.162)
R2	0.095	0.305	0.376	0.436
N	2099	2072	2072	1978

Note. p<0.01 ***; p<0.05 **; p<0.1*; standard errors in parentheses

This study draws on the results of the final Model (4) (also referred to as Basic PMT) in all further analysis below. The link-test[8] is insignificant and therefore we have strong evidence that the model is correctly specified. Further diagnostics for of the OLS estimation used in the study are presented in the appendix.

The R2 value of 0.436 in the estimation results above highlight that the performance of the model in predicting household welfare is well within the range of R Square typically observed in PMT literature. While Grosh and Baker (1995) presented R-squared from 0.3 to 0.4 for Latin American countries, Glinskaya and Grosh (1997) achieved an even lower R-Square of 0.2 for Armenia. Ahmed and Bouis (2002) obtained a result of 0.43 for their work in Egypt, while later studies with relatively higher predictive powers obtained R-square of 0.488 for Bosnia (The World Bank, 2009), 0.53 for Pakistan (Hou, 2008), 0.56 for SriLanka (Narayan & Yoshida, 2005) and 0.57 for Bangladesh (Sharif 2009). Particularly to Africa, PMT simulations carried out on Burkina Faso(0.64), Ethiopia(0.32), Ghana(0.56), Malawi(0.57), Mali(0.42), Niger(0.63), Nigeria(0.59), Tanzania(0.58), Uganda(0.49) give an average of R squared of 0.5 **(**Ravallion & Brown, 2016). Mills (2015) on a different set of African countries also includes PMT from Cameroon (Nguetse-Tegoum & Stoeffler, 2012) and Ghana with R-squared values of 0.61 and 0.55, respectively.

The parameters estimated in the regression for each variable included in the model are used as the respective weights for these characteristics to calculate a PMT score for each household. This means that instead of giving uniform weight to all welfare indicators, higher weights are given to those for which a unit change in value results in a higher change in household monthly consumption expenditure per adult equivalent. As can be seen from the results, while some indicators loose significance with the addition of more indicators, household head's characteristics of education and employment along with the household size, density of people in the house, urban proximity and number of orphans remain significant indicators of explaining a household's welfare. Similarly, the more easily verifiable categories of wall, floor and roof materials are also significant in the regression results.

[8] The link test is used after a regression to test for a specification error. If the model is correctly specified then _hat should be a statistically significant predictor, since it is the predicted value from the model. If the model is properly specified, the variable _hatsq shouldn't have much predictive power except by chance.

Since the scope of this research is to identify 'who' are the poor households instead of 'why' they are poor, the analysis of particular values of coefficients of each welfare determinant falls outside the scope. It is, however, worthy to note that the estimated results show that higher weights are given to household size, followed by higher levels of education and then household head's employment in business enterprises. While computer access followed by mobile phones are given higher weights among all other household assets included in the model, it can be seen that the proposed PMT is more likely to assign OVC transfers to households with poorer housing conditions, conventional materials for roof, walls and floor and ones using traditional sources of energy for cooking and lighting instead of those equipped with improved housing facilities.

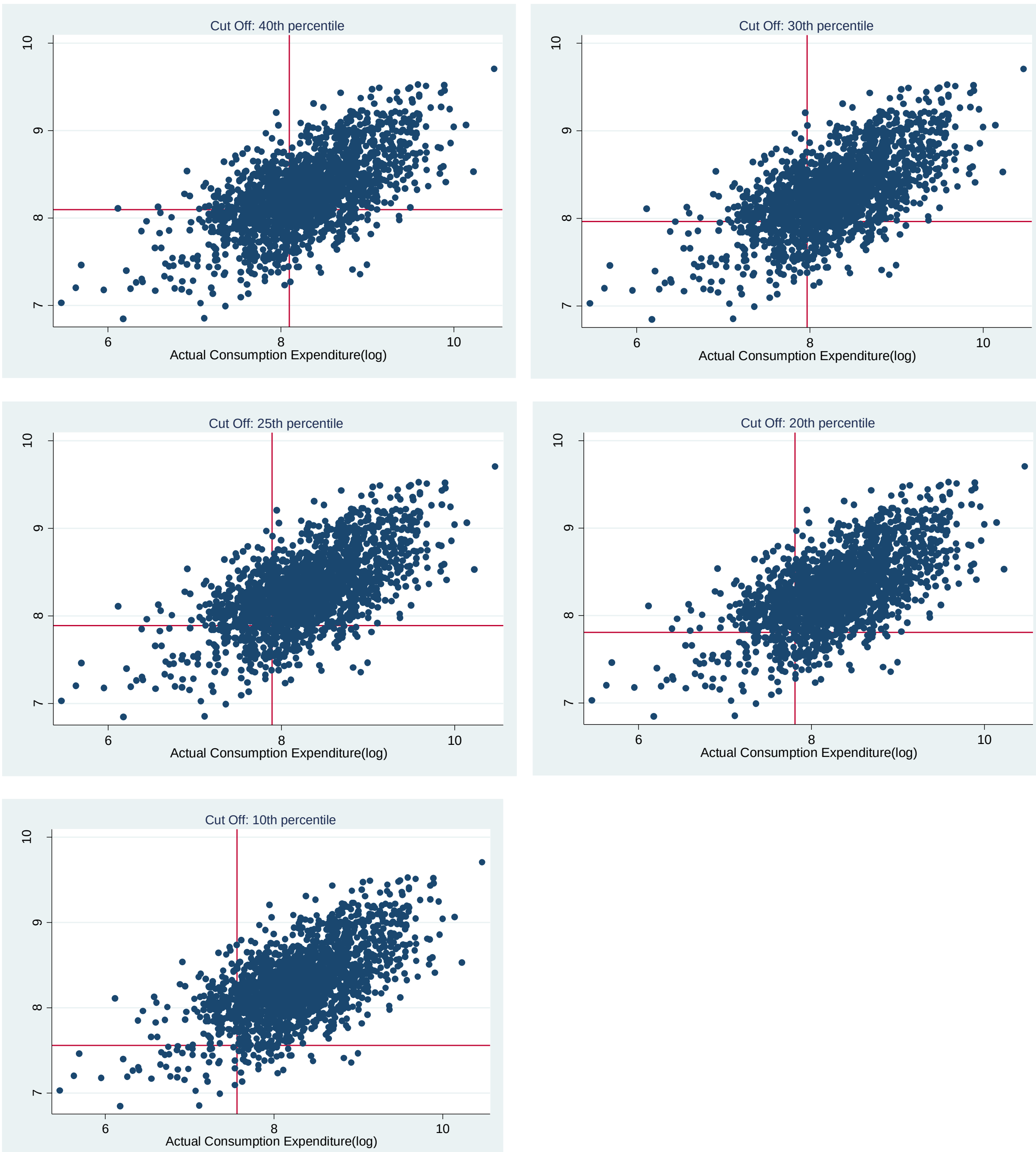
Targeting efficiency of the PMT is calculated by using the two most popular effectiveness measures namely inclusion and exclusion errors by calculating those erroneously included and those erroneously excluded from beneficiaries using the cut-offs at 40th, 30th, 25th, 20th and 10th percentiles of both, actual and predicted consumption expenditure. While these are the most commonly used poverty thresholds in PMT simulations, it is important to note that unlike most national level studies, this dissertation uses a particular backdrop of OVC households in Kenya so the refined sample population as shown in Section 4.1.2 essentially only contains households defined vulnerable on the basis of vulnerable children. Using a proxy means test is an "additional" layer to prioritize transfers to those who are monetarily poor amongst the OVC households. Therefore, since the sample included is of OVC households only, using cut-offs as low as 10th percentile would exclude 90% of an already vulnerable population based only on the monetary dimension.

Graphs in Figure 4 represent the scatterplot of predicted consumption expenditure against actual consumption expenditure in logged values with different cut offs. While all households to the left of the vertical poverty line (second and third quadrant) form the target group i.e. actual poor[9], all the ones below the horizontal poverty line (third and fourth quadrant) are the beneficiaries or eligible households i.e. those predicted as poor by the proposed PMT. Henceforth, the first and third quadrant highlight targeting successes i.e. non-poor households correctly identified as non-poor and poor households correctly identified as poor by the model, respectively. The forth quadrant however, highlights those erroneously included (inclusion error) whilst the second quadrant contains households erroneously excluded from the program (exclusion error). These errors in predictions increase as the cut-off is reduced to poorest percentiles highlighting that due to design errors discussed in detail below, PMT loses effectiveness when targeting the poorest of the poor.

[9] This notion is used in the dissertation to refer to households for which the true consumption expenditure falls below the poverty cut-off.

Figure 4.

Scatterplots showing a visual representation of actual and predicted poor at different poverty cutoffs



An in-depth analysis of calculation and distribution of inclusion and exclusion errors follows in Section 5.3. However before doing that, the subsection below aims to dissect the targeting coverage and incidence of the proposed PMT against a universally targeted cash transfer made to all OVC households in Kenya as well as the previously used Multi-Dimensional Poverty Indicating approach, which according to the baseline evaluation report by OPM (2008), predicted 95% of all OVC households as poor, nullifying the effectiveness of poverty targeting in the program's targeting mechanism (discussed in Chapter 3).

5.2. Incidence and Coverage of Proposed PMT

While the first layer of targeting has been applied by keeping only the OVC households in the sample, Table 8 shows the proportion of OVC households predicted to be poor using the proposed PMT at different cut-offs of actual consumption-expenditure.

Table 8.

Proportion of OVC households predicted as poor by PMT

Cut Off Score	Proportion of Population Predicted as Poor
10th percentile	0.044
20th percentile	0.105
25th percentile	0.146
30th percentile	0.196
40th percentile	0.304

Note. Author's calculations with cut-offs based on actual consumption expenditure percentiles

This shows that depending on the cut off used, the proposed proxy means test for targeting would extend coverage by predicting as much as 30% of the OVC households eligible for the transfer when the target group is specified as the lowest 40% of the actual consumption expenditure of the OVC households.

These results can be reasonably compared to the predictions for other African countries as in the results of Brown & Ravallion (2016) wherein the mean proportion of sample predicted to be poor using Basic PMT at a fixed poverty line of 20th percentile was 0.079 with the lowest results for Ethiopia (0.023) and highest for Nigeria (0.117) in comparison to 0.105 for 20th percentile for Kenyan OVC households in this research.

Analyzing where the OVC households predicted as poor fall on the actual expenditure, the results show that PMT performs markedly progressive in comparison to a uniform transfer. Table 9 shows the proportion of households selected as eligible by the proposed PMT, out of a certain consumption expenditure decile. Depending on what target group (poverty cut-off percentile) is chosen, as much as over 40 to 70% in the lowest decile are identified as eligible. Similarly, it can be seen that as many as all beneficiaries from the highest decile can be correctly excluded from the program using this targeting technique. Moreover, it can be seen that increasing target group from the lowest 20th percentile to 40th percentile more than doubles the proportion of the lowest expenditure decile to be selected as program beneficiaries. However, the advantage of larger shares of lowest deciles selected as beneficiaries in the program comes with the disadvantage of more beneficiaries coming from the higher deciles. While 20th percentile cut off shows a total of only 2.5% of the top 2 deciles as program beneficiaries against the 12% using 40th percentile, it comes with a 36% loss of poorest decile from 72% of them covered by the PMT at 40th percentile cut-off against 35% included at 20th percentile.

Table 9.

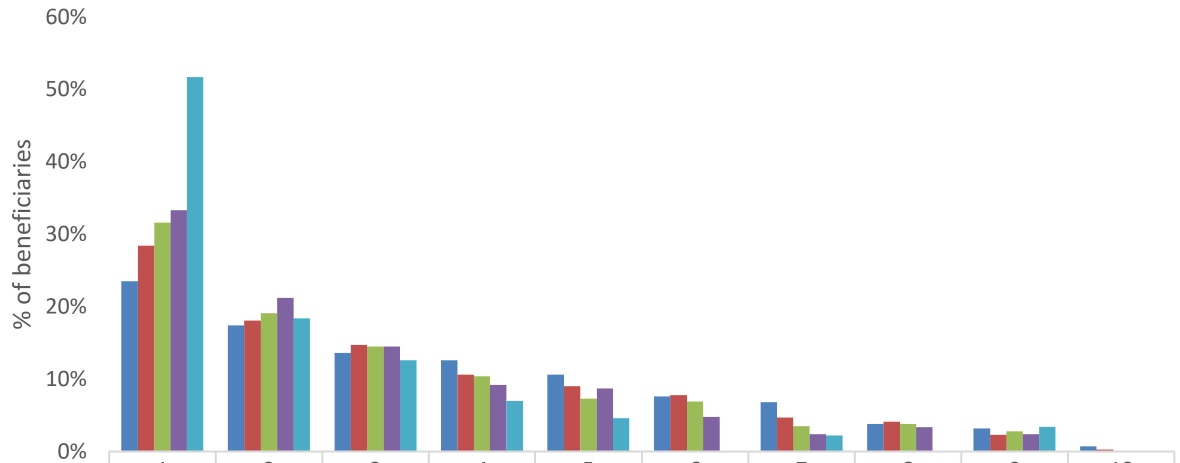
Coverage of PMT targeting by consumption deciles using cut-off percentiles at actual consumption expenditure

	Cut-Off Percentiles				
Decile	10th	20th	25th	30th	40th
1	0.228	0.350	0.462	0.558	0.716
2	0.080	0.221	0.276	0.352	0.523
3	0.056	0.152	0.212	0.290	0.414
4	0.030	0.096	0.152	0.207	0.384
5	0.020	0.091	0.107	0.178	0.323
6	0.000	0.051	0.101	0.152	0.232
7	0.010	0.025	0.051	0.091	0.207
8	0.000	0.036	0.056	0.081	0.116
9	0.015	0.025	0.041	0.046	0.096
10	0.000	0.000	0.000	0.005	0.020

An alternative approach to analyzing if PMT is ‘pro-poor’ in targeting is employed by evaluating the ‘incidence of targeting’ that measures proportions of the total selected beneficiaries as belonging to the respective expenditure quintiles.

Figure 5.

Incidence of targeting – distribution of total beneficiaries by their actual consumption-expenditure decile at different cut-offs



Cut offs	1	2	3	4	5	6	7	8	9	10
40th	24%	17%	14%	13%	11%	8%	7%	4%	3%	1%
30th	28%	18%	15%	11%	9%	8%	5%	4%	2%	0%
25th	32%	19%	15%	10%	7%	7%	4%	4%	3%	0%
20th	33%	21%	15%	9%	9%	5%	2%	3%	2%	0%
10th	52%	18%	13%	7%	5%	0%	2%	0%	3%	0%

The results in Figure 5 show that for all poverty cut-offs, larger percentage of selected beneficiaries belong to lower consumption-expenditure deciles, showing an overall progressive trend of targeting by the proposed PMT. Regardless of whichever poverty cut-off is employed, this targeting technique directs more transfers to poorer deciles instead of selecting an equal proportion of OVC households from each monetary group. While 54% of the predicted poor belong to the lowest expenditure quintile (bottom two deciles) when the poverty cut off is at 20th percentile, 2% come from the top two deciles. Benefits become significantly more concentrated to lowest expenditure deciles when low poverty cut-offs are chosen as seen from almost 90% of them belonging to bottom 4 deciles at 10th percentile cut-off. The distribution of beneficiaries becomes more widespread among consumption-expenditure deciles at higher poverty cut-offs where for instance at 30th percentile poverty threshold, around 70% of selected beneficiaries belong to bottom four deciles while the other 30% are distributed among the richer half of expenditure deciles.

The above results show that the coverage and incidence of targeting by proxy means test perform markedly better and are pro-poor against a uniform transfer to the selected vulnerable population. The following section calculates and analyzes the inclusion and exclusion error among those predicted as poor and those missed out from the program.

5.3. Inclusion and Exclusion Errors and Their Distribution

As discussed in Section 4.2.2**,** inclusion and exclusion errors form a part of PMT by design.

Calculated as shown in Table 10, both the inclusion and exclusion errors are inflated at all poverty cut-offs when set at actual instead of predicted consumption and the difference can therefore again be reemphasized as the additional coverage errors. This notion of additional coverage errors due to setting cut-offs lines at actual/true consumption expenditure is explained in the discussion of methodology in section 4.2.2**.** However, both inclusion and exclusion errors are lower for higher poverty cut-offs regardless of whether cut-offs are set using actual or predicted consumption expenditure. These results support that econometric targeting using Proxy Means Test reduces inclusion errors compared to those implied by uniform transfers. A universal transfer for a target population below the 20th percentile (0.2 coverage) would have the implied inclusion error of 0.8. This can be seen to be reduced to 0.45 using the proposed PMT. However, the increase in these errors at lower poverty thresholds reasserts that PMT loses its predictive power in identifying those who are very poor.

Table 10.

Inclusion and Exclusion Errors at different cut-offs specified according to actual and predicted consumption expenditure

	Cut-Off Basis			
	Actual Consumption Expenditure		Predicted Consumption Expenditure	
Cut Off Percentile	Inclusion Error	Exclusion Error	Inclusion Error	Exclusion Error
10th	0.482	0.771	0.477	0.739
20th	0.454	0.715	0.381	0.603
25th	0.406	0.654	0.366	0.557
30th	0.386	0.601	0.323	0.490
40th	0.328	0.489	0.295	0.391

Since it is inevitable to completely eliminate these two errors from PMT by design, the analysis below unpacks a further layer by examining the distribution of these errors in the OVC households. This approach is adopted because the impact of exclusion errors becomes relatively less concerning if most of the erroneously excluded households belong to deciles just below the poverty cut-off. Similarly, if those incorrectly included fall just above the poverty cut-off, the incidence of coverage is less concerning because households just below and just above the poverty cut-off are vulnerable to being switched to either side in face of minor shocks. As emphasized, this analysis becomes more relevant when the sample population altogether contains a refined sample of OVC households. This additional layer of PMT targeting in the Program's process can thus be deemed effective so long as the OVC households incorrectly predicted as non-poor (exclusion error) do not belong to the lowest deciles while those incorrectly predicted as poor(inclusion error) do not come from the richest deciles.

Table 11.

Distribution of inclusion and exclusion errors per consumption-expenditure decile at different cut-offs of actual consumption-expenditure

Deciles	**Cut-Off Percentiles**								
	10	20		25		30		40	
	Inclusion %	Inclusion %	Exclusion %	Inclusion %	Exclusion %	Inclusion %	Exclusion %	Inclusion %	Exclusion %
1			45.2		32.8		24.4		14.4
2	38.1		54.8		44.6		36.1		24.2
3	26.2	31.9		14.5	22.6		39.5		29.9
4	14.3	20.2		25.6		27.3			31.4
5	9.5	19.1		17.9		23.3		32.4	
6	0.0	10.6		17.1		20.0		23.4	
7	4.8	5.3		8.5		12.0		20.8	
8	0.0	7.4		9.4		10.7		11.7	
9	7.1	5.3		6.8		6.0		9.6	
10	0.0	0.0		0.0		0.7		2.0	
Total	100	100	100	100	100	100	100	100	100

Note. All those excluded at the cut-off of 10^{th} percentile are from the first decile since the poverty cut-off is at the poorest 10th percentile of actual consumption-expenditure

Table 11 highlights the distribution of those incorrectly missed and those incorrectly included as beneficiaries across consumption-expenditure deciles. While Table 10 presented high exclusion and inclusion errors, the results of Table 11 are encouraging as it can be observed that for all poverty cut-offs most households erroneously selected as or missed from beneficiaries lie in the deciles just above or just below the chosen poverty cut-offs, respectively. This analysis further corroborates the observation deducted in previous subsections that targeting through proxy means testing performs particularly effectively in reducing the inclusion errors as among those incorrectly included, no more than 10% belong to the top two consumption-expenditure deciles for all the poverty cut-offs chosen. These results provide the theoretical reasoning to propose Poverty -Weighted Regression in Section 5.4.

A similar analysis for distribution of inclusion and exclusion errors is conducted as per the geographic location of OVC households in rural and urban areas. Results in Table 12 show that for all poverty cut-offs most households incorrectly selected or incorrectly missed belong to the rural areas. While a mechanical reason for this can also be attributed to greater incidence of poverty in rural areas, it is also noteworthy to dissect rural OVC households as an extension to the basic PMT applied in the study. Figure 6 shows that 77.8% of the poorest 50% OVC households reside in rural areas of Kenya.

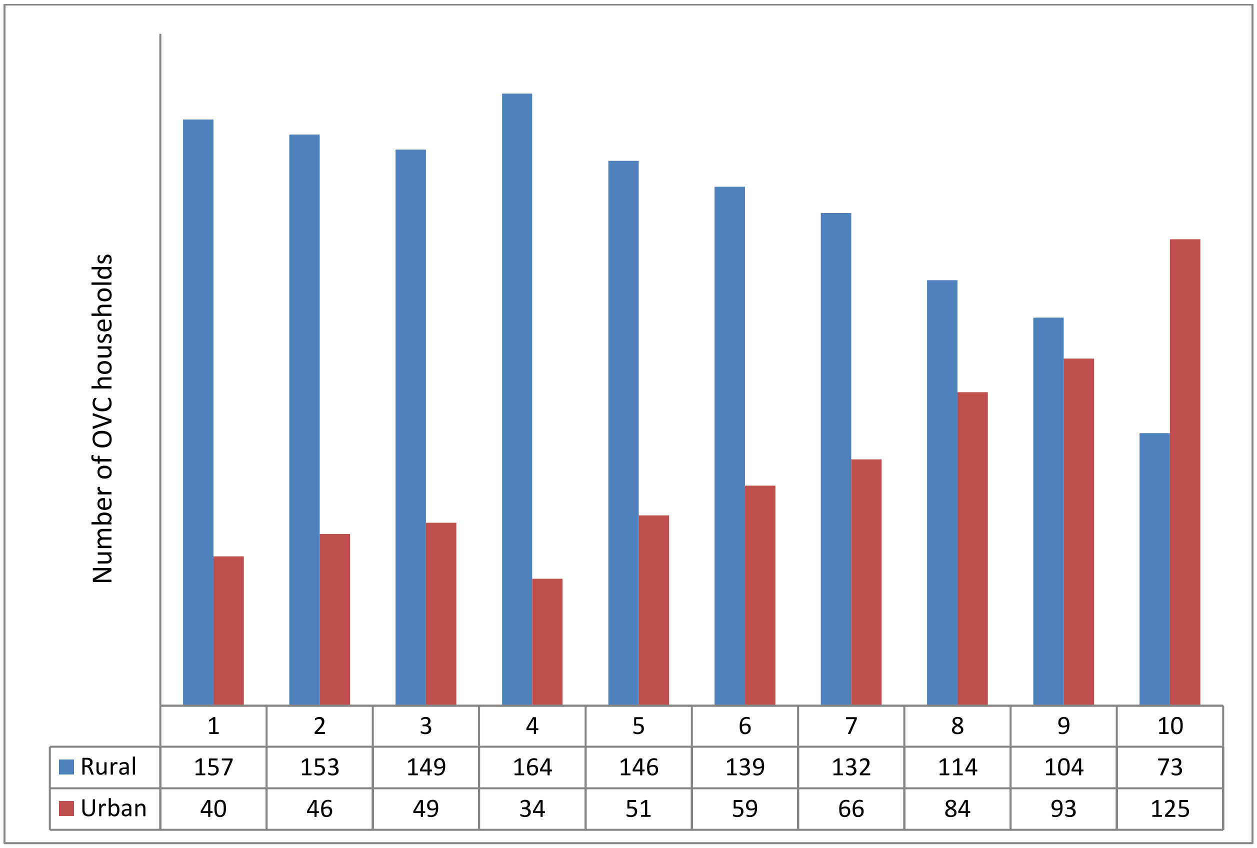
Table 12.

Distribution of inclusion and exclusion errors per location of OVC households a different cut-offs.

Location	Cut-Off Percentiles									
	10		20		25		30		40	
	Inc %	Exc %	Inc %	Exc %	Incl %	Exc %	Inc %	Exc %	Inc %	Exc %
Rural	92.8	73.9	90.4	73.9	88.0	71.2	88.7	69.5	86.7	69.3
Urban	7.1	26.1	9.6	26.1	11.9	28.8	11.3	30.5	13.2	30.7
Total	99.9	100	100	100	99.9	100	100	100	99.9	100

Figure 6.

Distribution of OVC households in each consumption-expenditure decile by location in rural or urban areas.



5.4. Extensions to Basic PMT

Using the analysis in Section 5.3, this study introduces two extensions to the basic PMT model presented in Section 5.1. These extensions draw heavily from the analytical approach adopted by Brown & Ravallion (2016) for nine African countries.

5.4.1. Poverty Weighted Least Squares

This subsection proposes an alternative to OLS estimation to predict the consumption-expenditure of OVC households in the form of Poverty Weighted Least Squares that entails placing higher weights on the squared errors of poorer people. Amongst the different weighting techniques, this study uses the approach presented by Mapa and Albis(2013), in which all observations below a poverty cut-off are equally weighed but those above the line are given zero weight. Essentially, only poor households are included in the regression following this approach.

However, using the analysis in Section 5.3 about the higher concentration of inclusion and exclusion errors around the chosen poverty cut-offs as the theoretical reasoning, and the empirical application of this rationale by Ravallion (2016), the PLS method is extended by including households marginally above the line. Once the parameters for each indicator are estimated, revised PMT scores are calculated. Two iterations for this are carried out in this study for the poverty cut-off at 20th and 40th percentile, separately. For the poverty cut-off at 20th percentile, along with households at or below the 20th expenditure percentile, the next 20% households as ranked by their consumption are also included in the regression. Similarly, the bottom 60% of the households are included in the regression carried out for the poverty cut-off set at 40th percentile.

The results of these iterations are presented in the Appendix (Table A3). The inclusion and exclusion errors are calculated at 20th and 40th percentile poverty cut-off using predicted consumption-expenditure from regressions with full weight on the bottom 40% and 60% of the OVC households ranked by consumption-expenditure.

The inclusion errors by this iteration perform slightly better than the population weighted average for the nine African countries in Brown & Ravallion (2016) wherein the average inclusion error for 20th percentile (using bottom 40%) and for 40th percentile cut-off (using bottom 60%) are computed to be 0.66 and 0.49, respectively. Conversely, the exclusion errors for this study fall above the country average of 0.164 and 0.042, at 20th and 40th percentile poverty cut-offs, as presented in Brown & Ravallion (2016).

Table 13.

Inclusion and Exclusion errors calculated by PLS run on bottom 40% and bottom 60% at poverty cut-offs at 20th and 40th percentile, respectively.

Sample	Cut-off Percentile	Inclusion Error	Exclusion Error
Bottom 60%	40th	0.31	0.07
Bottom 40%	20th	0.43	0.23

While weighted regressions help correctly include all actually poor (OVC households for whom the true consumption-expenditure falls below the poverty cut-off) represented by very low exclusion errors in Table 13, the inclusion errors remain high.

These results loop back to our reiterated finding that correctly maximizing the targeting of poor comes with an inevitable trade-off of some non-poor incorrectly included in the program. In this study, like other studies, when sample population is refined using another dimension of vulnerability other than income poverty, these inclusion errors are less harmful as the households incorrectly targeted also address some form of vulnerability.

5.4.2. Rural OVC Households Only

This extension to the Basic PMT model analyzed in 5.1 includes the OVC households located in rural areas of Kenya only. As seen in the analysis above, a significantly higher share of households defined as vulnerable according to OVC criteria lies in rural areas while with the largest share of lowest consumption-expenditure deciles, the incidence of income poverty is also concentrated in rural OVC households. Moreover, rural OVC households also form significantly higher share of those erroneously missed or erroneously included as shown in Table 12. Drawing on these observations, this subsection applies the Basic PMT but on rural households only. By doing so, this iteration essentially introduces another layer of in the existing targeting process of OVC Program (Section 3) of geographic targeting.

The purpose of this extension is to not support complete exclusion of urban households as doing so would mechanically exclude a high number of OVC households but in fact, to analyze the possible effectiveness of the proposed proxy means test on the inclusion and exclusion errors which are otherwise highly concentrated on this fraction of vulnerable households.

While Appendix (Table A3) shows the results of this simulation, the inclusion and exclusion errors calculated at 20th, 25th, 30th and 40th percentiles used as in the Basic PMT are shown in Table 14**.** These results show that when compared to applying the proposed PMT to the entire OVC population, an iteration for only the rural OVC households, decreases both inclusion and exclusion errors at all poverty cut-offs. While the gains in reducing inclusion and exclusion errors are modest when cut-offs are set according to actual consumption-expenditure percentiles, it performs markedly better in selecting all poor households at the lower cut-offs than the basic PMT when the cut-offs are set at percentile values using the consumption-expenditure predicted by the model in Section 5.1.

Table 14.

Inclusion and Exclusion Errors calculated by applying Basic PMT to rural OVC households only at different cut-offs.

	Cut-Off Basis			
	Actual Consumption Expenditure		Predicted Consumption Expenditure	
Cut-Off Percentile	Inclusion Error	Exclusion Error	Inclusion Error	Exclusion Error
20th	0.462	0.661	0.295	0.351
25th	0.401	0.610	0.316	0.390
30th	0.388	0.566	0.349	0.488
40th	0.318	0.443	0.385	0.560

While these extensions of the basic PMT employed in this study attempt to analyze the impact of targeting particular subgroups by consumption-expenditure or by location, the reduction in exclusion and inclusion errors, although modest, opens the possibility of improving targeting by ideally designing separate PMT models with welfare indicators more relevant to each of these subgroups. Although theoretically ideal and highly effective in ex-ante PMT simulations, doing so would entail higher administrative costs of data collection for Kenyan government.

The final subsection that follows provides robustness check for the basic PMT model proposed in this research.

5.5 Robustness of the Basic PMT

Since the predictions from the model are tested on the same observations that are used to derive the coefficients, the results may be bias in favor of the model – the possible problem of "over-fitting". In order to check for this, the study follows an approach similar to Sharif (2009) also applied in studies referred to in sections above (Grosh and Glinskaya, 1997; Hentschel et al., 2000; Hou, 2008). Using Stata, the sample is split randomly at household level and half of the households are assigned to the testing sample. The same PMT model is applied to this testing sample and inclusion and exclusion errors are calculated at different cut-offs. Table 15 and Table 16 show and compare these errors with the original PMT model at different cut-offs both at actual and predicted consumption-expenditure. Since, the inclusion and exclusion errors are not significantly different as compared to originally estimated, we can assert that the OLS estimation using the entire sample is quite robust.

Table 15.

Errors calculated by PMT on robustness test sample when compare to original model using cut-offs at percentile values of actual consumption expenditure

	Poverty Cut-Off Percentiles – using actual consumption expenditure							
	20^{th}		25^{th}		30^{th}		40^{th}	
	Inclusion	Exclusion	Inclusion	Exclusion	Inclusion	Exclusion	Inclusion	Exclusion
PMT Model	0.454	0.715	0.406	0.654	0.389	0.601	0.328	0.490
PMT Robustness	0.432	0.727	0.403	0.686	0.380	0.632	0.328	0.523

Table 16.

Errors calculated by PMT on robustness test sample when compare to original model using cut-offs at percentile values of predicted consumption expenditure.

	Poverty Cut-Off Percentiles – using predicted consumption expenditure							
	20^{th}		25^{th}		30^{th}		40^{th}	
	Inclusion	Exclusion	Inclusion	Exclusion	Inclusion	Exclusion	Inclusion	Exclusion
PMT Model	0.381	0.603	0.366	0.557	0.323	0.490	0.295	0.391
PMT Robustness	0.368	0.636	0.388	0.602	0.327	0.523	0.321	0.416

5.6. Limitations of the Study

Drawing on the caveats of the targeting criteria of OVC-Cash Transfer in Kenya as discussed in Chapter 3 and the implications of using OLS to run this simulation as discussed in Section 4.3, this subsection acknowledges the overall limitations of the study.

Although this study highlighted that targeting well-off orphans while excluding poor non-orphans in the current criteria of the OVC Cash transfer makes a strong case for proposing a design reorientation, an alternative approach was not proposed or taken up by the study. The primary focus of the study therefore remained a methodological understanding of PMT as a targeting technique. While this simulation adopts the popularly employed estimation technique of OLS estimation for the ease of interpretation, PMT calculations may suffer from the risk of endogeniety as the decisions of households about the explanatory variables are not fully independent of the decisions that determine welfare (the dependent variable of OLS). Moreover, although the R-square of model specified in this study falls in the average of existing literature, an iteration using separate set of indicators for rural and urban households can possibly increase the predictive power of the PMT. The variables on land and livestock ownership can have a significant role in explaining rural poverty. However, they could not be included in the Basic PMT nor the iteration for rural households due to sample estimation problems as data on very low number of OVC households was available.

Finally, since this exercise is a PMT simulation, the results of applying the different methodological choices as discussed are likely to be subjected to challenges and costs of implementation in real programs. An ex-poste analysis would therefore be extremely value-adding to compare with the results obtained from an ex-ante simulation as proposed in this study.

Chapter 6. Conclusion

This section distills lessons from the review of targeting mechanisms and the particular predictive exercise carried out to assess the effectiveness of targeting through proxy means testing. While no dearth of literature exists in suggesting that targeting performs better than universal transfers, both on fiscal and distributive grounds, the administrative and political difficulties to employ targeting techniques often lead to very high ‘cracks’ or errors in the process that challenge the very idea of directing transfers to poor instead of providing universal assistance.

It is also important to understand that no-one-fits-all recipe of a perfect targeting method exists as the choice of various administrative, self and community based targeting techniques is not binary but lies on a continuum with advantages and caveats for each technique. Assessing the effectiveness of a targeting method, is, therefore only a part of assessing the effectiveness of an assistance or aid program because programs may have objectives other than targeting poorest of the poor (e.g. maximizing the beneficiaries) that may involve trade-offs with targeting performance. This emphasizes the need for policy makers, governments and donor agencies to develop a thorough understanding of a multitude of targeting methods at both individual and household level to strike a combination that optimizes the gains on per dollar value of transfers.

Initiated and widely applied in Latin America, proxy means testing has become an increasingly popular econometric targeting in social protection. While the technique is essentially applied in case when actual income or expenditure is not available or is extremely costly to collect, the use of econometrically predicted welfare instead of actual welfare of households introduces inevitable inclusion and exclusion errors in the methodology by default. Using household survey data, this study ran a simulation of PMT particularly using a sample population of households with orphans and vulnerable children in Kenya as the initial poverty targeting mechanism used in the Program was deemed ineffective and was replaced by a more sophisticated proxy means testing. The proposed set of indicators used in the regression to proxy for household welfare explain about 43% of variation in consumption expenditure, which lies in the average of previous PMT studies. Depending on what poverty cut-off basis are used, the results of the proposed PMT in the dissertation finds out inclusion and exclusion errors of 35-40% and 50-60% on average, respectively. Because of the high values of these errors, the emphasis of analysis has been the incidence and coverage of targeting, as well as the distribution of these errors to dissect if PMT targeting is in fact progressive in nature. This is because although poverty targeting is the aspect taken up in this study, it is noteworthy to not lose track that the main objective of Cash Transfer of Orphan and Vulnerable Children is to address not just monetary poverty but direct benefits to households defined as the target group on the grounds of child vulnerability. This to highlight that as the trade-off between targeting performance may seem more relevant in this case study, the impact of exclusion and inclusion errors is less concerning when households incorrectly missed or included do not belong to the poorest and richest of OVC households, respectively.

The results of such an approach are encouraging because proxy means testing helps eliminate as much as 50% of inclusion errors otherwise implied by including all OVC households in the program. This, however, comes with a repeatedly emphasized trade-off with households incorrectly excluded from being selected as eligible for the transfer.

In the analysis of the methodological effectiveness of proxy means testing, this study also finds out that significant differences can be observed when making different methodological choices such as setting not only different levels of poverty cut-offs but also whether these cut-offs are established using actual or predicted consumption expenditure values. For all percentile cut-offs, basing them on actual consumption expenditure values result in inflated inclusion and excluded errors due to additional coverage errors.

While the proposed methodology and analysis can robustly and easily be replicated to other assistance programs to analyze the predictive power of a PMT model ex-ante, some interesting areas falling beyond the scope of this research but noteworthy for future research in the area are worth mentioning. Adding another layer of geographic targeting and carrying out a PMT model by refining a set of separate welfare indicators including land and livestock ownership for rural population of Kenya holds an opportunity to significantly reduce exclusion errors due to a significantly high concentration of OVC households in rural parts of the counties. Moreover, looping back to the initial motivation of the dissertation, the evaluation of any proposed PMT can certainly gain more leverage when assessed against data on actual beneficiaries. Not only would this give a more realistic appreciation of what PMT can achieve, the cleavages in the implementation processes and their impact on the intended incidence can be explored in depth.

This research, hereabove, concludes with the aspiration of contributing to a better understanding of the methodological discretions in proxy means testing to evaluate the inherent trade-offs and hence helping policy makers and practitioners making improved and more informed decisions in targeting not only the OVC-Cash Transfer programs in Kenya but any assistance schemes.

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Appendix

A.1. Characteristics of OVC households by disaggregated categories of welfare indicators

Figure A1. *Distribution of sample OVC households by disaggregated categories of wall material used*

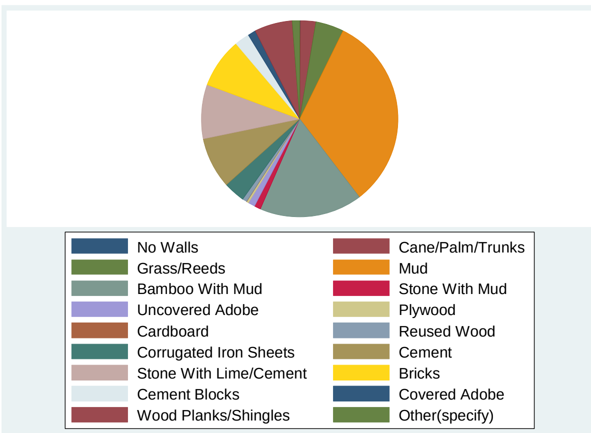


Figure A2. *Distribution of sample OVC households by disaggregated categories of roof material used*

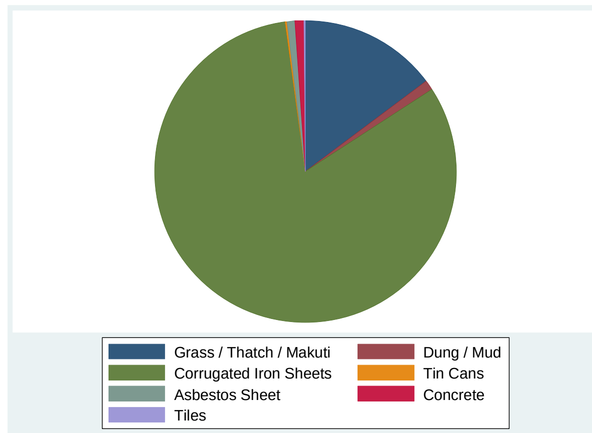


Figure A3. *Distribution of sample OVC households by disaggregated categories of floor material used*

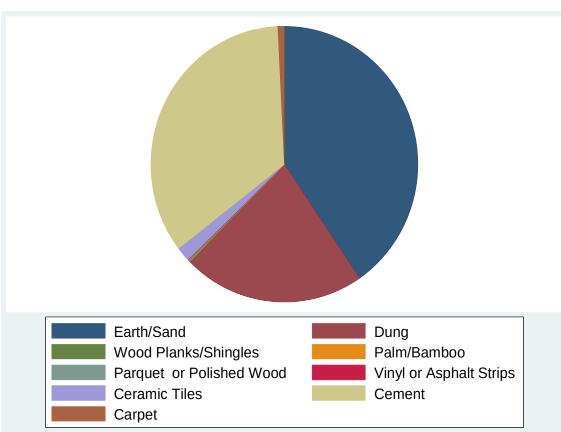


Figure A4. *Distribution of sample OVC households by disaggregated categories of drinking water source*

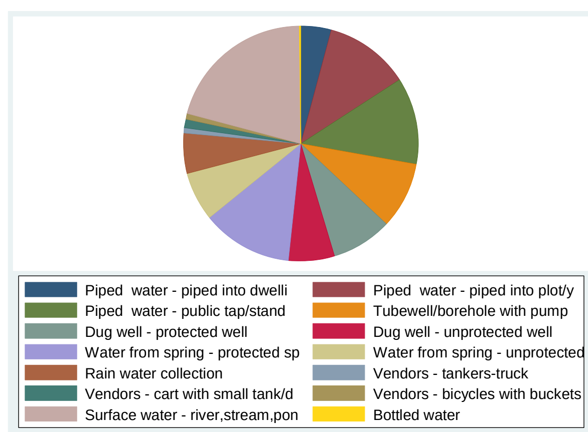


Figure A5.*Distribution of sample OVC households by disaggregated categories of energy source-lighting*

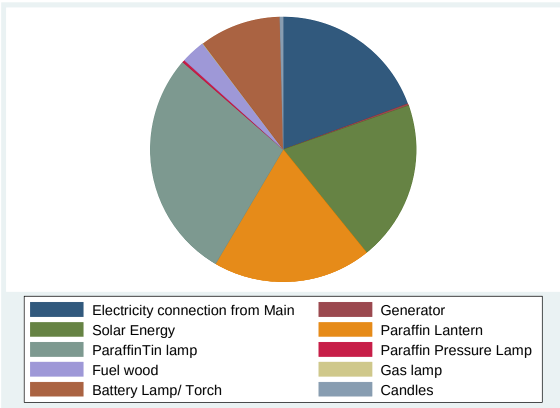
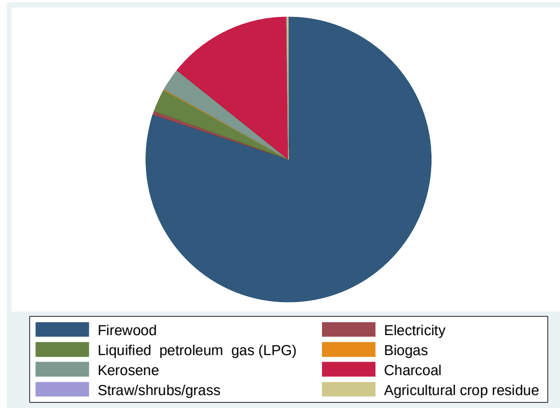


Figure A6. *Distribution of sample OVC households by disaggregated categories of energy source- cooking*



A.2 Diagnostics for Basic PMT

Table A1

Link Test for Basic PMT

Log_ConsumptionExpenditure	Coeff	Standard Error	p>|t|
_hat	1.952	1.120	0.081
_hatsq	-0.057	0.066	0.391
_constant	-3.96	4.71	0.400

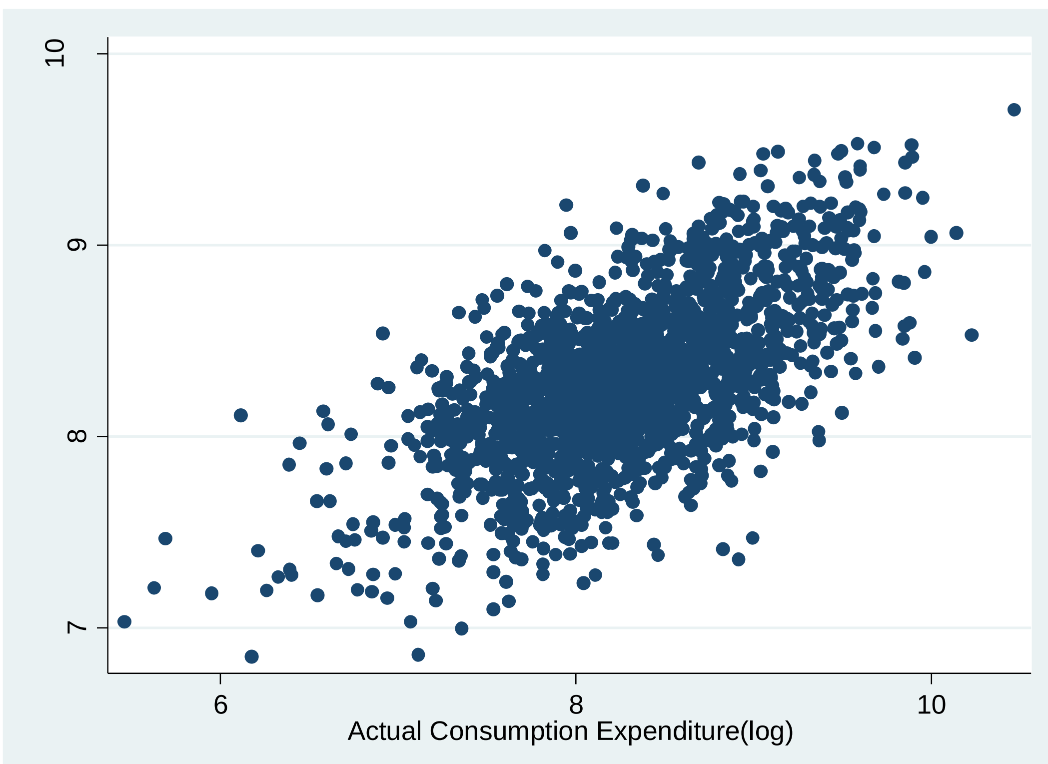
Table A2

VIF for Basic PMT

Mean VIF	8.95

Figure A7

Scatterplot of fitted values for Basic PMT



Note. A model with perfect prediction would reflect all households lying on a 45 degree straight line from bottom left to top right with all predicted values essentially identical to the actual consumption expenditure.

A.3. Regression Results for Extensions to Basic PMT

Table A3.

Regression Results for Basic PMT when applied to the bottom 40% and bottom 60% for PLS regression as well as when applied to the rural OVC households only.

	Bottom 40	**Bottom 60**	**Rural Households**
	PLS _ 1	**PLS_2**	
Location: Urban	-0.010 (0.030)	0.060** (0.030)	-
Household Characteristics			
HHhead gender : male	0.028 (0.033)	-0.013 (0.028)	0.032 (0.033)
HHhead education: no education *omitted*			
HHhead education: pre-primary and primary	-0.009 (0.036)	-0.013 (0.030)	-0.019 (0.042)
HHhead education: post primary and above	0.023 (0.045)	0.059* (0.036)	0.089* (0.051)
HHhead employment: wage	0.035 (0.035)	0.018 (0.032)	0.0120 (0.039)
HHhead employment: business enterprise	0.024 (0.041)	0.001 (0.034)	0.102** (0.043)
HHhead employment: own or rented farm	0.070** (0.031)	0.057** (0.028)	0.096*** (0.034)
HHhead age	0.000 (0.001)	0.001 (0.001)	-0.001 (0.001)
Household size: less than five	0.078** (0.027)	0.059** (0.025)	0.174*** (0.035)
Number of people per room	-0.022** (0.009)	-0.031*** (0.008)	-0.052*** (0.011)
Number of orphans in house: greater than one	-0.018 (0.030)	-0.033 (0.026)	-0.063* (0.030)
Access to additional assets			
Television : yes	-0.027 (0.068)	-0.001 (0.051)	0.119* (0.069)
Computer: yes	-0.114 (0.055)	0.165** (0.070)	0.290** (0.113)
Mobile Phone: yes	0.119*** (0.034)	0.131*** (0.031)	0.215*** (0.039)
Internet: yes	-0.061 (0.054)	-0.009 (0.044)	0.081 (0.052)
House Characteristics			

Own house: yes	0.053 (0.061)	0.028 (0.052)	0.083 (0.066)
Walls: cement/brick/corrugated iron	0.029 (0.028)	0.002 (0.026)	0.125*** (0.040)
Floor: No floor/Earth/Sand *omitted*			
Floor: Dung/Bamboo	0.061 (0.108)	0.147 (0.095)	0.253*** (0.096)
Floor: Wood/Tiles/Cement/Carpet	0.277*** (0.073)	0.191*** (0.067)	0.100 (0.082)
Roof: Grass/Makuti *omitted*			
Roof: Dung	0.097 (0.137)	0.043 (0.143)	0.041 (0.157)
Roof: Corrugated Iron/Concrete/Tiles	0.096* (0.060)	0.129** (0.055)	0.115* (0.062)
Toilet Facility: no facility/bucket *omitted*			
Toilet Facility: flushed to piped server/septic tank/pit	0.225** (0.086)	0.212*** (0.067)	0.245** (0.109)
Toilet Facility: latrine (with or without slab)	0.077 (0.050)	0.057 (0.165)	-0.023 (0.050)
Drinking water unit: outside the living facility	0.006 (0.037)	0.051 (0.032)	-0.026 (0.058)
Main source of energy for cooking: other than firewood	0.011 (0.050)	0.036 (0.062)	0.090 (0.068)
Main source of energy for lighting: fuel-wood/candles *omitted*			
Main source of energy for lighting: Electricity from mains	0.559*** (0.132)	0.612*** (0.126)	0.662*** (0.138)
Main source of energy for lighting: Generator/Solar Energy	0.532*** (0.123)	0.615*** (0.120)	0.644*** (0.125)
Main source of energy for lighting: Parrafin Lamps(Lantern/Tin/Pressure)	0.501*** (0.119)	0.575*** (0.117)	0.571*** (0.120)
Main cooking appliance: other than traditional firestone	0.048 (0.036)	0.026 (0.035)	0.104** (0.045)
Floor-Roof Interaction			
Dung Floor* Dung Roof	-0.352** (0.175)	0.075 (0.216)	0.060 (0.180)
Dung Floor*Iron/Concrete/Tile Roof	-0.097 (0.115)	-0.213** (0.100)	-0.300*** (0.104)
Cement/Tile Floor* Dung Roof	0	0	0
Cement/Tile Floor *	-0.313***	-0.231***	-0.183**

Iron/Concrete/Tile Roof	(0.084)	(0.074)	(0.091)
Constant	6.940***	7.029***	7.28***
	(0.162)	(0.150)	(0.176)
R2	0.302	0.289	0.360
N	792	1187	1331