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Operational Poverty Targeting by Proxy Means Tests
Models and Policy Simulations for Malawi

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OPERATIONAL POVERTY TARGETING BY PROXY MEANS TESTS

MODELS AND POLICY SIMULATIONS FOR MALAWI

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ABBREVIATIONS AND ACRONYMS

AISP	Agricultural Input Subsidy Program
BEAM	Basic Education Assistance Module
COICOP	Classification of Individual Consumption According to Purpose
FAO	Food and Agriculture Organization
EGS	Employment Guarantee Scheme
FIVIMS	Food Insecurity and Vulnerability Mapping System
GAPVU	Gabinete de Apoio à População Vulnerável
GDP	Gross Domestic Product
GoM	Government of Malawi
HDI	Human Development Index
HIPCs	Heavily Indebted Poor Countries
HPI	Human Poverty Index
IFPRI	International Food Policy Research Institute
IHS1	First Malawi Integrated Household Survey
IHS2	Second Malawi Integrated Household Survey
INAS	National Institute for Social Welfare
JCE	Junior Certificate of Education
KCAL	Kilocalorie
KG	Kilogram
LPM	Linear Probability Model
LSMS	Living Standard Measurement Survey
MASAF	Malawi Social Action Fund
MDGs	Millennium Development Goals
MK	Malawi Kwacha
MPRS	Malawi Poverty Reduction Strategy
MSCE	Malawi School Certificate of Education
NGOs	Non Governmental Organizations
NPK	Nitrogen Phosphorus and Potassium (Fertilizer)
NSO	National Statistics Office

OLS	Ordinary Least Square
PAM	Program Against Malnutrition
PMS	Poverty Monitoring System
PMT	Proxy Means Tests
PPP	Purchasing Power Parity
PPS	Probability Proportional to Size
PROGRESA	Programa de Educacion, Salud y Alimentacion
PSLC	Primary School Leaving Certificate
PSU	Primary Sampling Units
PWP	Public Work Program
SAS	Statistical Analysis System
SISBEN	Sistema de Identificación de Beneficiarios
SPI	Starter Pack Initiative
ROC	Receiver Operating Characteristic
TLU	Tropical Livestock Unit
UN	United Nations
UNDP	United Nations Development Program
USAID	United States Agency for International Development
WL	Weighted Logit
WLS	Weighted Least Square

Operational Poverty Targeting by Proxy Means Tests

Models and Policy Simulations for Malawi

EXECUTIVE SUMMARY

There is a long standing belief that accurate targeting of public policy can play a major role in alleviating poverty and fostering pro-poor economic growth. Many development programs fail to reach the poor in that a sizeable amount of program benefits leak to higher-income groups and a substantial proportion of poor are excluded. This is also the case in Malawi, one of the poorest countries in Sub-Saharan Africa. In response to widespread poverty and endemic food insecurity, the country decision makers enacted various programs, including free food, food-for-work, cash-for-work, subsidized agricultural inputs, etc. To target these programs at the poor and smallholder farmers in the country, policy makers rely mainly on community-based targeting systems in which local authorities, village development committees, and other community representatives identify program beneficiaries based on their assessment of the household living conditions. However, most of these programs have been characterized by poor targeting and significant leakage of benefits to the non-poor due to a number of factors, including various local perceptions, favoritism, abuse, lack of understanding of targeting criteria, political interests, etc. Almost all interventions are poorly targeted in the country.

Therefore, this research explores potential methods and models that might improve the targeting efficiency of agricultural and development policies in the country. Using the Malawi Second Integrated Household (IHS2) survey data and a variety of estimation methods along with stepwise selection of variables, we propose empirical models for improving the poverty outreach of agricultural and development policies in rural and urban Malawi. Moreover, the research analyzes the out-of-sample performances of different estimation methods in

identifying the poor and smallholder farmers. In addition, the model robustness was assessed by estimating the prediction intervals out-of-sample using bootstrapped simulation methods.

Furthermore, we estimate the cost-effectiveness and impacts of targeting the poor and smallholder farmers. It is often argued that targeting is cost-ineffective and once all targeting costs have been considered, a finely targeted program may not be any more cost-efficient and may not have any more impact on poverty than a universal program. We assess whether this is the case using household-level data from Malawi. More importantly, we evaluate whether administering development programs using the newly developed models is more target- and cost-efficient than past agricultural subsidy programs namely the 2000/2001 Starter Pack and the 2006/2007 Agricultural Input Support Program (AISP).

Estimation results suggest that under the newly designed system, mis-targeting is considerably reduced and the targeting efficiency of development policies improves compared to the currently used mechanisms in the country. Findings indicate that the estimation methods applied achieve the same level of targeting performance. The rural model achieves an average poverty accuracy of about 72% and a leakage of 27% when calibrated to the national poverty line of 44.29 Malawi Kwacha (MK). On the other hand, the urban model yields on average a poverty accuracy of about 62% and a leakage of 39% when calibrated to the same poverty line. The results are also confirmed by the Receiver Operating Characteristic (ROC) curves of the models which show that there is no sizeable difference in aggregate predictive accuracy between the estimation methods. The ROC curve is a powerful tool that can be used by policy makers and project managers to decide on the number of poor a program or development policy should reach and ponder on the number of non-poor that would also be wrongly targeted.

Calibrating the models to a higher poverty line improves its targeting performances, while calibrating the models to a lower line does the opposite. For example, under the international poverty line of US$1.25 (i.e. MK59.18 in Purchasing Power Parity), the rural model covers about 82% of the poor and wrongly targets only 16% of the non-poor, whereas the urban model covers about 74% of the poor and wrongly identifies 26% of the non-poor. On the other hand, using an extreme poverty line of MK29.81 disappointingly reduces the model's poverty accuracy and leakage: the rural model yields a poverty accuracy of 51% and a leakage of 39% while the urban model yields a poverty accuracy of about 48% and a leakage of 68%. Furthermore, a breakdown of targeting errors by poverty deciles indicates that the models perform well in terms of those who are mistargeted; covering most of the poorest deciles and excluding most of the richest ones. These results have obvious desirable welfare implications for the poor and smallholder farmers. It is all important to mention that the models selected cannot explain but predict poverty. A causal relationship should not be inferred from the results.

There is compelling evidence in favor of targeting since considering all costs does not make targeting cost- and impact-ineffective. Findings suggest that the new system is considerably more accurate and more target-efficient than the currently used mechanisms for targeting agricultural inputs in the country. Likewise, simulation results indicate that targeting the poor and smallholder farmers is more cost- and impact-effective than universal coverage of the population. Better targeting not only reduces the Malawian Government's direct costs for providing benefits, but also reduces the total costs of a targeted program. Though administrative costs increase with finer targeting, the results indicate that the overall benefits outweigh the costs of targeting. Likewise, finer targeting reduces the costs of leakage by a sizable margin and produces the highest impacts on poverty compared to universal regimes. However, the finest redistribution does not consistently yield the best transfer efficiency, nor does it consistently improve post-transfer poverty.

Furthermore, the newly designed system appears to be more cost-efficient than the 2000/2001 Starter Pack and the 2006/2007 Agricultural Input Support Program (AISP). While the Starter Pack and the AISP transferred about 50% of total transfer, under the new system about 73% of transfer is delivered to the poor and smallholder farmers. Likewise, under the new proxy system the costs of leakage are cut down by 55% and 57% for the Starter Pack and AISP, respectively. Thus, under the new system it is possible to reduce leakage and undercoverage rates and improve the cost and transfer efficiency of development programs in the country.

The proxy indicators selected reflect the local communities' understandings of poverty and include variables from different dimensions, such as demography, education, housing, and asset ownership. These indicators are objective and most can be easily verified. However, the collection of information on those indicators might entail an effective verification process. Likewise, the emphasis put on proxy means tests in this research does not imply that other potential targeting methods should be disregarded. Indeed, proxy means tests are not perfect at targeting; the system developed can be combined with other methods in a multi-stage targeting process. Furthermore, targeting can be a politically sensitive issue; the system developed does not take into account the reality that policy makers, program managers, or development practitioners may adjust eligibility criteria due to political, administrative, budgetary, or other reasons.

The models developed can be used in a wide range of applications, such as identifying the poor and smallholder farmers, improving the existing targeting mechanisms of agricultural input subsidies, assessing household eligibility to welfare programs and safety net benefits, producing estimates of poverty rates and monitoring changes in poverty over time as the country and donors cannot afford the costs of frequent household expenditure surveys, estimating the impacts of development policies targeted to those living below the poverty line, and assessing the poverty outreach of microfinance institutions operating in the country. This broad range of applications makes the models potentially interesting policy tools for the country. However, the models developed are not sufficient. They must also be coupled with investments in education, rural infrastructure, economic growth related sectors, and strong political will to impact on the welfare of Malawian people.

The research also provides a framework for developing and evaluating a simple and reasonably accurate system for reaching the poor and smallholder farmers in Malawi, but the methodology can be useful in other areas of applied research and replicated in other developing countries with similar targeting problems.

Operationelle Armutsbekämpfung durch *Proxy Means Tests*

Modelle und Politik Simulationen für Malawi

ZUSAMMENFASSUNG

Es ist eine generell akzeptierte Annahme, dass öffentliche Politikmaßnahmen eine wichtige Rolle bei der Armutsbekämpfung und bei der Entwicklung von Wirtschaftswachstum spielen können. Als Antwort auf die weitverbreitete Armut und endemische Ernährungsunsicherheit haben die Entscheidungsträger Malawis verschiedene Programme, insbesondere die Subventionierung landwirtschaftlicher Betriebsmittel, die ein wichtiges Element der Entwicklungspolitik des Landes darstellen, entwickelt. Um diese Programme gezielt auf die Armen und Kleinbauern des Landes auszurichten, bauen die Verantwortlichen meist auf gemeindebasierte Systeme bei denen lokale Behörden Programmbegünstigte auf Basis der Beurteilung der jeweiligen Lebensbedingungen der Haushalte identifizieren.

Die meisten dieser Programme sind jedoch durch eine schlechte Zielgenauigkeit gekennzeichnet und hohe Anteile des Nutzens der Programme gehen aufgrund verschiedener Faktoren, darunter lokale Vorstellungen, Vetternwirtschaft, Missbrauch, Mangel an Verständnis für die Zielkriterien, politische Interessen etc, irrtümlicherweise an Nicht-Arme. Fast alle Maßnahmen im Land leiden unter einer unzureichenden Zielgenauigkeit.

Daher untersucht diese Arbeit potenzielle Methoden und Modelle, die die Zielgenauigkeit von Agrar- und Entwicklungsmaßnahmen des Landes verbessern können. Darüber hinaus schätzen wir die Kosteneffektivität und Auswirkungen einer Fokussierung auf Arme und Kleinbauern. Es wird häufig argumentiert, dass zielgruppengenaue Programme nicht kosteneffektiv sind und dass, wenn sämtliche Kosten der Zielgruppenfindung berücksichtigt werden, ein gut abgestimmtes zielgruppenorientiertes Programm nicht kosteneffizienter wäre und keine größeren Effekte auf die Armutsreduzierung hätte als ein generelles Programm. Wir

untersuchen diese These anhand von Haushaltsdaten aus Malawi. Darüber hinaus bewerten wir, ob die Administration und Durchführung von Entwicklungsprogrammen mit Hilfe der neu entwickelten Modelle zielgruppengenauer und kosteneffizienter ist als bisherige Programme zur Subventionierung von landwirtschaftlichen Betriebsmitteln, insbesondere das *Starter Pack* von 2000/2001 und das *Agricultural Input Support Program* (AISP) von 2006/2007.

Unter Verwendung von Daten des Malawi *Second Integrated Household Survey* (IHS2) und einer Reihe von Schätzmethoden mit schrittweiser Auswahl von Variablen entwickeln wir empirische Modelle zur Verbesserung der Armutsminderung durch Agrar- und Entwicklungsprogramme im ländlichen und städtischen Malawi. Zusätzlich analysiert die Arbeit die über die Stichprobe hinausgehende Güte der verschiedenen Modelle bei der Identifizierung der Armen und Kleinbauern. Die Robustheit der Modelle wurde darüber hinaus mit Hilfe von Bootstrapping-Simulationen für die Vorhersageintervalle außerhalb der Stichprobe geschätzt.

Die Schätzergebnisse legen nahe, dass mit dem neuentwickelten System eine fehlgerichtete Ausrichtung erheblich reduziert werden kann und dass die Zielgruppenausrichtung von Entwicklungsmaßnahmen im Vergleich zu bisher im Land genutzten Mechanismen verbessert werden kann. Die Ergebnisse legen nahe, dass die angewendeten Schätzmethoden alle die gleiche Zielgenauigkeit erreichen. Das ländliche Modell erreicht bei Kalibrierung auf die nationale Armutslinie eine Genauigkeit bei der Erreichung von Armen von 72% und ein Durchsickern an Nichtzielgruppen von 27%. Auf der anderen Seite erreicht das städtische Modell im Durchschnitt eine Zielgruppengenauigkeit von 62% und ein Durchsickern von 39% (ebenfalls bei Kalibrierung auf die nationale Armutslinie). Diese Ergebnisse werden ebenfalls durch die *Receiver Operating Characteristic* (ROC) Kurven der Modelle bestätigt, die keine beträchtlichen Unterschiede zwischen der aggregierten Vorhersagegenauigkeit der Schätzmodelle zeigen. Die ROC-Kurve ist ein mächtiges Werkzeug das von Programmverantwortlichen und Projektmanagern zur Entscheidungsfindung darüber genutzt werden kann, wieviele Arme ein Programm oder eine Entwicklungsmaßnahme erreichen soll und wieviele fälschlicherweise begünstigte Nicht-Arme gefördert werden.

Die Kalibrierung der Modelle auf eine höhere Armutslinie verbessert ihre Zielgenauigkeit, während eine Kalibrierung auf eine niedrigere Linie zum Gegenteil führt. Zum Beispiel erreicht das ländliche Modell bei Verwendung der internationalen Armutslinie von 1,25 USD (d.h. MK 59,18 PPP) etwa 82% der Armen und fördert fälschlicherweise nur 16% der Nicht-Armen. Auf der anderen Seite verschlechtert die Verwendung einer extremen Armutslinie von MK 29,81 die Genauigkeit und das Durchsickern der Modelle: Das ländliche Modell erzielt eine Armutsgenauigkeit von 51% und ein Durchsickern von 39% während das städtische Modell eine Genauigkeit von 28% und ein Durchsickern von 68% erreicht. Darüber hinaus deutet ein Herunterbrechen der Fehlausrichtungen nach Armutsdezilen an, dass die Modelle in Bezug auf die fälschlicherweise Begünstigten gut funktionieren: Sie decken die meisten der ärmsten Dezile ab, während die meisten der reichsten Dezile nicht berücksichtigt werden. Diese Ergebnisse haben naheliegende wünschenswerte Wohlfahrtseffekte für Arme und Kleinbauern. Es ist wichtig zu erwähnen, dass die ausgewählten Modelle Armut nicht erklären sondern lediglich voraussagen können. Ein kausaler Zusammenhang kann auf Grundlage der Ergebnisse nicht hergestellt werden.

Es bestehen zwingende Anhaltspunkte zu Gunsten von Zielgruppenorientierung da auch die Berücksichtigung sämtlicher Kosten die Zielgruppenorientierung nicht kosten- und ergebnisineffizient werden lässt. Die Ergebnisse legen nahe, dass das neue System erheblich genauer und zieleffizienter ist als der bisher verwendete Mechanismus zur zielgruppengenauen Programmgestaltung für landwirtschaftliche Betriebsmittel. Ebenso deuten die Simulationsergebnisse an, dass die Fokussierung auf Arme und Kleinbauern kosten- und ergebniseffektiver ist als eine globale Erfassung der gesamten Bevölkerung. Bessere Zielgruppenausrichtung verringert nicht nur die direkten Kosten der Regierung

Malawis für unterstützende Maßnahmen sondern reduziert auch die Gesamtkosten eines Programms. Obwohl die administrativen Kosten mit genauerer Zielgruppenausrichtung ansteigen, zeigen die Ergebnisse, dass die Vorteile insgesamt die Kosten überwiegen. Ebenso verringert eine genauere Ausrichtung die Kosten für das Durchsickern in großem Maßstab und sorgt für die größten Auswirkungen auf die Armut verglichen mit generellen Verfahren. Mit steigender Genauigkeit der Ausrichtung erhöht sich jedoch weder in jedem Fall die Verteilungseffizienz, noch verringert sich in jedem Fall die Folgearmut.

Weiterhin scheint das neu entwickelte System kosteneffizienter zu sein als das *Starter Pack* von 2000/2001 und das *Agricultural Input Support Program* (AISP) von 2006/2007. Während das *Starter Pack* und das *AISP* etwa 50% sämtlicher Mittel an Arme und Kleinbauern verteilen, erreichen unter dem neuen System etwa 73% der Mittel Arme und Kleinbauern. Ebenso werden unter dem neuen System die Kosten des Durchsickerns um 55% gegenüber dem *Starter Pack* und um 57% gegenüber dem *AISP* gesenkt. Unter dem neuen System ist es daher möglich, Durchsickern und Fehlallokation zu verringern und die Kosten- und Verteilungseffizienz von Entwicklungsprogrammen des Landes zu verbessern.

Die ausgewählten Indikatoren spiegeln das Armutsverständnis lokaler Gemeinden wider und beinhalten demografische Variablen ebenso wie Bildung, Lebensverhältnisse und Eigentum. Diese Indikatoren sind objektiv und die meisten können leicht verifiziert werden. Die Sammlung von Informationen bezüglich dieser Indikatoren könnte jedoch effektiv einen Überprüfungsprozess darstellen. Es sollte erwähnt werden, dass der Schwerpunkt in dieser Arbeit zwar auf *Proxy Means Tests* gelegt wurde, was aber nicht impliziert, dass andere mögliche Methoden zur Zielgruppenfokussierung abgelehnt werden sollten. *Proxy Means Tests* sind tatsächlich nicht einwandfrei bei Armutsidentifizierung und das entwickelte System kann in einem Mehrstufenprozess mit anderen Methoden kombiniert werden. Zielgruppenfokussierung kann darüber hinaus eine politisch sensible Angelegenheit sein; das entwickelte System berücksichtigt nicht die Tatsache, dass Programmverantwortliche und Projektmanager oder Entwicklungshelfer die Kriterien zur Anspruchsberechtigung aufgrund von politischen, verwaltungs- und haushaltsbezogenen oder anderen Gründen anpassen.

Die entwickelten Modelle können in einem weiten Spektrum von Fällen verwendet werden, z.B. bei der Identifizierung von Armen und Kleinbauern, bei der Verbesserung bestehender Vergabemechanismen für subventionierte landwirtschaftliche Betriebsmittel, bei der Beurteilung der Anspruchsberechtigung von Haushalten, zur Schätzung von Armutshöhe und beim Monitoring von Armutsveränderungen im Zeitverlauf. Da sich das Land und Geldgeber die Kosten häufiger Untersuchungen zu den Lebenshaltungskosten der Haushalte oft nicht leisten können, sind die Modelle auch hilfreich bei der kostengünstigen Schätzung der Auswirkungen von Entwicklungsprogrammen die auf Bedürftige unterhalb der Armutslinie abzielen und bei der Beurteilung der Armutsbekämpfung von im Land tätigen Mikrofinanzinstitutionen. Diese große Bandbreite von Anwendungen lässt die Modelle zu potenziell interessanten Politikinstrumenten für das Land werden. Die entwickelten Modelle sind jedoch nicht ausreichend. Sie müssen einhergehen mit Investitionen in Bildung, ländliche Infrastruktur, Wirtschaftswachstum in verwandten Wirtschaftssektoren und mit einem starken politischen Willen, die Wohlfahrt der Bevölkerung Malawis zu steigern.

Diese Arbeit stellt ein Grundgerüst für die Entwicklung und Bewertung eines einfachen und recht genauen Systems zur Identifizierung von Armen und Kleinbauern in Malawi bereit, doch die Methodik kann auch in anderen Bereichen angewandter Forschung nützlich sein und kann in anderen Entwicklungsländern mit ähnlichen Problemen bei der Zielgruppenfokussierung repliziert werden.

Ciblage Opérationnel de la Pauvreté et des Politiques de Développement

Modéles et simulations appliqués au Malawi

RESUME

Le ciblage des politiques de développement et des régimes sociaux en faveur des petits agriculteurs et des pauvres est considéré depuis fort longtemps comme crucial pour réduire la pauvreté et soutenir une croissance économique pro-pauvre. Le ciblage consiste à concentrer les resources limitées dont disposent les Etats et les bailleurs de fonds sur les pauvres et ceux qui ont le plus besoin d'une assistance au sein de la population. C'est donc un moyen plus efficace et moins coûteux de lutte contre la pauvreté. Le ciblage effectif est devenu impératif avec l'avènement des programmes d'ajustement structurels dans les années 80 et plus récemment de la crise financière internationale qui a contraint beaucoup de pays en développement à réduire de facon drastique les dépenses publiques.

Le Malawi est sans doute l'un des pays les plus pauvres en Afrique au sud du Sahara avec un taux de pauvreté de 52,4% en 2005. En réponse à une pauvreté endémique et à l'insécurité alimentaire grandissante, les décideurs politiques Malawites ont initié plusieurs programmes sociaux et de développement tels que les aides alimentaires, les travaux publics à haute intensité de main-d'oeuvre et les subventions agricoles (engrais, semences, etc.) qui constituent une politique de choix en matière d'amélioration des conditions de vie des ménages dans le pays. Pour identifier les bénéficiaires de ces programmes que sont les petits agriculteurs et les pauvres, les décideurs politiques recourent principalement au ciblage communautaire qui permet aux autorités, représentants locaux et comités villageois de développement de sélectionner ces bénéficiaires en se basant sur l'évaluation de leurs conditions de vie.

Cependant, plusieurs études ont montré que la plupart de ces programmes sont charactérisés par un ciblage médiocre des pauvres et une fuite considérable de resources vers les ménages les plus riches et les plus politiquement influents. De surcroît, l'evaluation des programmes de subvention en intrants agricoles a montré que ces programmes ont creé des distortions considérables au niveau des marchés car une bonne partie de ces subventions est alloueé par erreur aux agriculteurs riches qui pourraient autrement acquérir les intrants au prix du marché, causant ainsi une substitution des intrants commerciaux aux intrants subventionnés. En outre, tous les acteurs s'accordent à reconnaître que la plupart des interventions en faveur des pauvres sont très mal ciblées dans le pays. Cet état de choses est lié à plusieurs raisons dont la méconnaissance des pauvres, la différence dans les perceptions locales de la pauvreté, le favoritisme, la corruption, une connaissance inadéquate des critères de sélection des bénéficiaires, les interférences politiques, etc.

Ainsi, cette recherche a exploré les modèles et méthodes pouvant améliorer le ciblage des programmes de développement et des services sociaux dans le pays. En se basant sur les données de la 2ième enquête intégrée des ménages au Malawi (IHS2-2005) et différents outils économétriques, l'étude propose des modèles empiriques conçus à partir d'indicateurs socio-économiques qui identifient et ciblent plus précisément les pauvres et les petits agriculteurs dans le pays. Par ailleurs, nous avons conduit des tests de validation hors échantillon et estimé les limites de prédictions à l'aide des méthodes de rééchantillonnage communément appelées *bootstrap*.

En outre, nous avons évalué à l'aide de simulations, l'efficience et l'effet d'un meilleur ciblage sur la pauvreté. Dans les débats sur le ciblage de la pauvreté, il est souvent soutenu que toute considération faite des coûts liés au ciblage, un régime bien ciblé sur les pauvres serait inefficient et n'aurait pas plus d'effet qu'un régime universel qui déssert toute la population. La présente recherche a constaté si cette thèse est fondée ou non. Par ailleurs, l'étude a comparé l'efficience des modèles établis aux performances des programmes de subventions agricoles dans le pays.

Les résultats de l'étude suggèrent qu'avec les modèles établis, les erreurs de ciblage peuvent être considérablement réduites. De plus, l'analyse revèle que les différentes méthodes d'estimation utilisées ont atteint les mêmes performances lorsque validées hors échantillon. Le modèle rural a produit une précision moyenne d'environ 72% en termes de ciblage des pauvres et une erreur de 27% en faveur des non-pauvres lorsqu'il est calibré au seuil national de pauvreté de 44,29 Malawi Kwacha (devise du Malawi). Autrement dit, le modèle rural identifie correctement 72% des ménages pauvres et confond 27% des ménages non-pauvres aux pauvres. Cependant, le modèle urbain a produit une précision de 62% en termes de ciblage des pauvres et une erreur d'identification de 39% au sein des ménages non-pauvres lorsqu'il est calibré au même seuil de pauvreté. Ces résultats sont confirmés par les courbes ROC «Receiver Operating Characteristic» des modèles qui montrent qu'il n'y a pas de différence substantielle entre les méthodes d'estimation utilisées. La méthodologie ROC permet de comparer le pouvoir prédicteur des méthodes d'estimation et des modèles établis. C'est aussi un outil très puissant pouvant permettre aux décideurs et coordonnateurs de projets de fixer la part des ménages pauvres à cibler par les politiques anti-pauvreté et de mesurer les erreurs de ciblage correspondantes.

Par ailleurs, un calibrage à l'aide d'un seuil de pauvreté plus élevé que le seuil national améliore les performances des modèles, mais un calibrage avec un seuil de pauvreté plus bas réduit ces performances. Par exemple, sous le seuil de pauvreté international de 1,25 dollars US, le modèle rural couvre environ 82% des ménages pauvres et produit une erreur d'inclusion de 16% seulement. Par contre, sous le seuil de pauvreté extrême de 29,81 Malawi Kwacha, le modèle rural identifie correctement 51% seulement des ménages pauvres et produit une erreur d'inclusion de 39% au sein des ménages non-pauvres. Néanmoins, une

déssagréggation des erreurs de ciblage par niveau de pauvreté indique que ces erreurs décroissent avec l'augmentation du niveau de consommation. En effet, les résultats d'analyse montrent que quel que soit le seuil de pauvreté appliqué, tous les modèles établis ont ciblé plus de pauvres dans les déciles inférieurs et moins de pauvres dans les déciles supérieurs. Il en découle que ces modèles couvrent mieux les plus pauvres parmi les pauvres. Ces résultats ont des implications sociales désirables pour les programmes de développement.

Les résultats d'analyse montrent par ailleurs qu'un meilleur ciblage des ménages pauvres, toute considération faite des coûts, n'est inefficicient ni en termes de coûts ni en termes d'effets sur la pauvreté. En effet, l'étude suggère que les modèles établis sont considérablement plus précis et plus efficients que le ciblage communautaire actuellement utilisé pour identifer les bénéficiaires des subventions agricoles au Malawi. Les différentes simulations effectuées démontrent également qu'une couverture universelle des ménages est très coûteuse et inefficiente comparée au ciblage à l'aide des modèles établis. Un meilleur ciblage réduit non seulement les dépenses publiques, mais aussi les coûts totaux des programmes de développement. Bien qu'une amélioration du ciblage de la pauvreté s'accompagne d'un accroissement des coûts administratifs, l'analyse indique que le bénéfice global dépasse les coûts d'un programme bien ciblé vers les pauvres. Il ressort également de l'étude qu'un meilleur ciblage réduit de facon substantielle les coûts liés aux erreurs de ciblage et produit un impact bien plus fort sur la pauvreté comparé au régime universel.

L'étude a également révélé que l'utilisation des modèles établis est plus efficient non seulement en termes de ciblage, mais aussi en termes de coûts comparée aux performances des programmes de subventions agricoles au Malawi. Alors qu'environ 50% des subventions agricoles ont été effectivement transférés aux agriculteurs pauvres, un ciblage basé sur les nouveaux modèles permet de transférer jusqu'à 72% des resources aux pauvres. De même, les coûts liés aux erreurs de ciblage sont réduits de plus de 50% avec les nouveaux modèles.

Ainsi, l'application des modèles établis permettrait de réduire de facon significative les erreurs de ciblage des pauvres et d'améliorer l'efficience des programmes et politiques de développement au Malawi. Toutefois, un ciblage très affiné ne produit pas toujours les meilleures performances en termes de coûts et d'effets.

Les indicateurs de pauvreté utilisés pour l'établissement des modèles réflètent les perceptions locales de la pauvreté. Ces indicateurs sont pour la plupart objectifs et faciles à vérifier. Cependant, pour limiter la fraude et la corruption pendant la phase de sélection, le ciblage de la pauvreté à l'aide des modèles établis nécéssiterait la mise en place d'un système de vérification de l'information livrée par les ménages. De plus, l'accent particulier mis sur les modèles de ciblage à base d'indicateurs de pauvreté (*proxy means tests*) dans cette recherche n'implique pas que les autres méthodes de ciblage doivent être ignorées. En effet, les modèles conçus ne sont pas parfaits. Ils peuvent donc être combinés avec d'autres méthodes de ciblage pour davantage d'efficacité.

Les modèles établis peuvent être appliqués à la résolution d'un ensemble de problèmes de développement, telles que l'identification des ménages et des petits agriculteurs pauvres au Malawi, l'amélioration de l'efficience du système de ciblage des subventions agricoles, l'évaluation de l'accès des ménages démunis aux services sociaux et au microcrédit, le suivi de l'évolution de la pauvrété; ce qui permet de réduire les coûts de collecte fréquente des données sur les dépenses de consommation, l'estimation de la couverture sociale des institutions de microfinance et de l'impact des politiques de lutte contre la pauvreté. Ces applications font des modèles établis des outils privilégiés au service des décideurs au Malawi.

Cependant, ces modèles uniquement ne sont pas suffisants. En effet, le ciblage des actions de développement en faveur des ménages pauvres peut être politiquement sensible; les modèles développés dans cette étude ne prennent pas en compte les réalités politiques au niveau des décideurs et des coordonnateurs des programmes de développement qui pourraient modifier les critères de sélection des pauvres pour diverses raisons: politiques, administratives, budgétaires, etc. Il importe également que le ciblage effectif des pauvres soit couplé avec des investissements adéquats dans les secteurs moteurs de la croissance, l'éducation, l'infrastructure rurale et une volonté politique forte pour améliorer le bien-être des Malawites.

La présente recherche a aussi établi un cadre méthodologique pour le développement et l'évaluation des modèles de ciblage de la pauvreté. Il est cependant impérieux de souligner que les modèles développés ne sont pas explicatifs de la pauvreté mais peuvent seulement servir à prédire la pauvreté et le statut des ménages. Enfin, les différentes méthodes d'estimation utilisées peuvent être aussi appliquées dans d'autres pays en développement ayant des problèmes similaires de ciblage des pauvres et des petits agriculteurs.

OPERATIONAL POVERTY TARGETING BY PROXY MEANS TESTS

MODELS AND POLICY SIMULATIONS FOR MALAWI

CHAPTER I

1. INTRODUCTION

1.1 Background to the Research

Eradicating poverty is one of the major challenges facing the developing world and the international community. The plethoric number of National, International, Non-Governmental Organizations, and advocacy groups fighting poverty on all its dimensions around the world just indicates the extent of the challenge.

More than one billion of people in the developing world live in absolute poverty (UN, 2009). Three out of four people in developing countries live in rural areas and most of them depend directly or indirectly on agriculture for their livelihood (World Bank, 2008). While, the Asian and Latin American countries have made significant progress in reducing poverty in the past decades, the results have been rather mixed in sub-Saharan Africa and the poverty rate remained above 50% in 2005 (UN, 2009). Most of the countries in the region also suffer from heavy external debt burdens due to a combination of factors, including inappropriate development policies, imprudent external debt management policies, lack of perseverance in structural adjustment and economic reform, deterioration in their terms of trade, and poor governance. They have been classified as Heavily Indebted Poor Countries - HIPCs - (World Bank, 2009a).

Furthermore, the performance of agriculture in sub-Saharan Africa has been unsatisfactory, especially when contrasted with the green revolution in South Asia (World Bank, 2008). In the mid-1980s, cereal yields were comparably high. Fifteen years later in South Asia, yields had increased by more than 50% and poverty had declined by 30%. In sub-Saharan

Africa, yields and poverty were unchanged. Likewise, food security remains challenging for most countries in Africa, given low agricultural growth, rapid population growth, weak foreign exchange earnings, and high transaction costs in linking domestic and international markets.

The persistence of mass poverty and hunger in this region of the world is rightly seen not only as a major ethical and political problem, but also as a serious threat to macro-economic stability and long-term development. In the wake of this threat, the international community devised the Millennium Development Goals (MDGs), one of which is to halve extreme poverty on all its forms between 1990 and 2015. However, progress has been rather slow and even reverse. Previous estimates suggest that little progress was made in reducing extreme poverty in Sub-Saharan Africa (UN, 2008). With the recent economic downturn, major advances against extreme poverty are likely to have stalled (UN, 2009). Increases in the price of food have had a direct and adverse effect on the poor. In 2009, an estimated 55 million to 90 million more people will be living in extreme poverty than anticipated before the crisis. Likewise, the encouraging trend in the eradication of hunger since the early 1990s was reversed in 2008, largely due to higher food prices which have pushed 100 million people deeper into absolute poverty (UN, 2008). A decrease in international food prices in the second half of 2008 has failed to translate into more affordable food for most people around the world. The prevalence of hunger in developing regions is now on the rise, from 16% in 2006 to 17% in 2008. Most of this increase will occur in sub-Saharan Africa and Southern Asia, which are the poorest regions of the world.

One of the major reasons of this persistent poverty and food insecurity is the low targeting efficiency and poverty outreach of most development programs in these countries. There is a growing recognition from the development community that many existing development and safety net programs are very badly targeted (Coady and Parker, 2009). Over the past few decades, development projects failed to either reach the poor or meet their aspirations and needs in developing countries. Therefore, policy makers as well as international donors are making conscious efforts to ascertain whether the projects they fund actually reach the poor. To this end, they have begun to take concrete steps to direct their financial and technical support to those programs that have greater poverty outreach and withdraw resources from those programs that fail to reach the poor (Zeller et *al.*, 2006a). Better targeting has become an imperative for developing countries in the wake of macroeconomic and structural adjustment programs under which governments are pressured to cut back enormously on their expenditures (Chinsinga, 2005).

Moreover, the success of any development policy or project will hinge on a key factor: the extent to which they actually target and reach the poor. Excellent health or education projects make little dent in poverty alleviation if the poor fail to access them, imaginative poverty-based or income transfer policies will not have served their purpose if they are misdirected to the non-poor (Zeller et *al.*, 2006a). Ideally, targeting should help direct resources to those who need them the most, i.e. the poor. In theory, a better targeting should result in a redistribution of resources to the poor by directing resources only to them. Thus, targeting is a means of increasing program efficiency by increasing the benefit that the poor can get within a fixed budget. It allows for the most effective use of limited government and donor resources and it is likely to result in higher marginal impact given that the poor might be more efficient in using scarce resources than the less poor. Likewise, historically public spending tends to exclude the lower strata of the population. Therefore, without active efforts to target resources at the poor, even the so-called "universalist programs" will miss the poor (Grosh, 2009).

Furthermore, the literature suggests that countries with more egalitarian income distribution may perform better in terms of growth and poverty reduction than those with high income inequality (Ravallion, 1997, Thorbecke and Charumilind, 2002). Thus, better targeting may foster economic growth. Achieving the MDGs also requires targeting areas and population groups that have clearly been left behind – rural communities, the poorest households and ethnic minorities (UN, 2009).

1.2 Problem Statement

By all estimates, Malawi is a very poor country with 52.4% of its population living below the poverty line and 22% living in extreme poverty (National Statistics Office - NSO - , 2005a). In other words, about 6.4 million Malawians live in poverty and as many as 2.7 million Malawians, about one in every five people, live in such dire poverty that they cannot afford to meet even their recommended daily food needs (Government of Malawi - GoM - and World Bank, 2007). The country is one of the poorest in Sub-Saharan Africa with over 80% of its workers in the primary sector, most in agriculture (Benson, 2002).

The proportion of poor people living in poverty is highest in rural areas of the southernmost (64%) and northernmost (56%) parts of the country, which are also the most densely populated rural regions, while the center is relatively less poor (47%). Urban areas have much lower percentages of people living below the poverty line (25%), and they also have the lowest share of ultra-poor (8%). Although poverty incidence rates are relatively high in most areas of the country, there is a considerable differentiation in poverty levels within districts. Nevertheless, poverty is pervasive in the country. Due to improved macroeconomic management, favorable weather conditions, and a supportive donor environment, in the last 3-4 years, the country has experienced high growth rates averaging 7.5% and the growth rate is projected at 6.9% in 2009 (World Bank, 2009c).

In the past, public services, such as agricultural extension and market infrastructure as well as resources, such as credit, fertilizer and improved seeds, etc. distributed through the existing public social safety net systems financed by international donors and the national government, were not efficiently targeted at the poor, nor to their aspirations and needs as shown by various studies (World Bank, 2006, 2007; Smith, 2001). Estimates from the IHS2 survey data of 2005 suggest that about 35% of the rural poor did not benefit from the targeted Starter Pack Initiative, whereas 62% of the rural non-poor reported benefiting from the program. Likewise, researches by Ricker-Gilbert and Jayne (2009) and Dorward et *al.* (2008) suggest that the 2006/2007 Agricultural Input Subsidy Program (AISP) has been targeted to wealthier and politically connected farmers who would otherwise have purchased the fertilizer, causing substantial displacements on the fertilizer market. Almost all social protection programs are poorly targeted in the country (GoM and World Bank, 2007).

As a result, poverty has not been reduced in the country. From 1998 to 2005, the poverty rate declined less than 2% from 54.1% to 52.4%. Moreover, extreme poverty has not substantially been reduced during the same period. However, poverty has not been static. The frequent and widespread occurrence of shocks in Malawi results in large movements into and out of poverty. Such volatility at the household level reflects the pervasive risks and shocks which affect the lives of Malawians. Recent trends in human development indicators broadly support the conclusion that there has been no or little progress in reducing poverty in the country since 1998. Furthermore, given the lack of progress during the past decade, Malawi is unlikely to achieve the target reduction in poverty and ultra-poverty by 50% between 1990 and 2015 (GoM and World Bank, 2007).

With a per capita income of US$230 (World Bank, 2008) and limited donor resources, the surplus available to redistribute is relatively small. Meanwhile, the large proportion of the population living under the poverty line means that any program large enough to have a substantial impact on the poor would be extremely costly and affordable options will only be able to reach some fairly limited portion of the population in need, and will have limited effect on household welfare (Smith, 2001). Better targeting can maximize the reduction of poverty given a limited budget for poverty alleviation and the trade-off between the number of beneficiaries covered by an intervention and the level of transfer - i.e. an opportunity cost -

(Coady et *al.*, 2002). Therefore, it is important that assistance is not mistakenly given to the non-poor, who may attempt to gain access to benefits by misrepresenting their income status (Glewwe, 1992).

It has appeared that much more remains to be done or corrected to ensure that development interventions reach their intended beneficiaries in the country. A major challenge for Malawi is to develop a low cost, fairly accurate, and easy system to target the poorest (PMS, 2000). Therefore, we conduct research on the theme: *Operational Poverty Targeting by Proxy Means Tests: Models and Policy Simulations for Malawi.*

The study intends to make innovative methodological and practical contributions to the econometric estimation of poverty assessment models. Especially, we would like to establish whether indicator-based targeting offers a better prospect compared to the currently used mechanisms for targeting the poor and smallholder farmers, largely dominated by community-based targeting in Malawi. In addition to the Weighted Least Square (WLS), we employ the Weighted Logit and Weighted Quantile regressions with refined econometric methods for testing a model's robustness and out-of-sample validity. Furthermore, we estimate the cost-effectiveness and poverty impacts of targeting and assess whether using the models developed is more target- and cost-efficient than past agricultural subsidy programs, namely the targeted Starter Pack Initiative and the Agricultural Input Support Program (AISP). Hence, the development of advanced poverty models is expected to improve existing targeting methods used by the Malawian Government and donors in agricultural and rural development. Efficiently targeting the poor is likely to improve the household food security, agricultural production, and contribute to the country's overall agricultural development in the long run.

1.3 Research Objectives and Scope of the Study

The overall objective of this research resides in developing low cost and fairly accurate models for targeting the poor and smallholder farmers and assessing the cost-effectiveness and poverty impacts of targeting in Malawi. Findings from the study should help to improve the targeting of development policies and social safety net funds towards the poor and smallholder agricultural households.

From the theoretical point of view, the research should contribute to the ongoing international research on poverty assessment and earlier works by the International Food Policy Research Institute (IFPRI), the World Bank, the Food Insecurity and Vulnerability Information and Mapping Systems (FIVIMS) of the Food and Agriculture Organization (FAO), and the project of the IRIS Center at the University of Maryland in Asia, Latin America, and Africa. Particularly, the analysis is expected to improve the above-mentioned works through the use of more refined econometric models as well as improved techniques for testing model's robustness and out-of-sample validity.

The study seeks to answer the following questions:

1. What are the best sets of indicators (models) – both in terms of accuracy and practicality – for correctly predicting whether a household is poor or not?
2. How well do the models perform out-of-sample, i.e. in an independent sample?
3. How sensitive are the models to the poverty line?
4. Is there a difference between estimation methods in terms of predictive power or targeting accuracy?
5. Is targeting by proxy means tests more target- and cost-efficient than universal interventions and community-based targeting?
6. What are the potential benefits and impacts of targeting by proxy means tests?

Specifically, this research seeks to achieve the following objectives:

1. identify the best sets of indicators for predicting the household poverty status;
2. perform robustness tests to assess the predictive power of the identified sets;
3. estimate the prediction intervals for the model performances;
4. evaluate the model sensitivity to different poverty lines;
5. estimate the cost-effectiveness and benefits of targeting by proxy means tests;
6. simulate the potential impacts of targeting under a proxy means test on poverty;
7. compare the model targeting efficiency to the performance of the Starter Pack and AISP programs;
8. discuss the potential contributions of the models and their implications for targeting development policies in Malawi and other developing countries.

1.4 Organization of the Thesis

This thesis is organized as follows. Section 1.5 describes the data used for the research, whereas section 1.6 reviews the literature on targeting, including the definition and nature of poverty and past targeted programs in Malawi.

We address the research questions within the scope of three research articles. In the first article titled: *Operational Models for Improving the Targeting Efficiency of Development Policies: A systematic comparison of different estimation methods using out-of-sample tests* (Chapter 2), we apply two regression methods – the Weighted Least Square and Weighted Logit – along with stepwise selection of variables to develop different proxy means tests models for urban and rural Malawi. Both estimation methods are compared based on their targeting performances out-of-sample and their Receiver Operating Characteristic (ROC) curves. Furthermore, the model sensitivity to the poverty line is examined and the major conclusions regarding the use of the models and its contributions to improving the targeting efficiency of Malawi's development policies are drawn.

The second paper is similar to the first one. However, in contrast to the first paper which uses continuous as well as dummy variables, the second paper titled: *Targeting the Poor and Smallholder Farmers: Empirical evidence from Malawi* (Chapter 3) uses only categorical poverty indicators and applies a stepwise logit to develop simple models for identifying the poor and smallholder farmers in the country. Categorical indicators are less prone to measurement errors than continuous variables. Indicators are selected based on a set of statistical instruments, including the area under a ROC curve which is a good measure of how well an indicator predicts poverty. To facilitate the screening of beneficiaries and the models use on the field, subsequent transformations are applied after estimation and the key findings are highlighted.

The third paper which is titled: *To Target or Not To Target? The costs, benefits, and impacts of indicator-based targeting* (Chapter 4), estimates the cost-effectiveness, the benefits, and poverty impacts of targeting. It is often argued that targeting is cost-ineffective and once all targeting costs have been considered, a targeted program may not be any more cost-efficient and may not have any more effect on poverty than a universal program. We test whether this is the case for Malawi. Using a weighted Quantile regression, the paper develops proxy means test models for Malawi and assess whether targeting is more cost- and impact-effective compared to universal interventions. In addition, the potential benefits of targeting are simulated. Furthermore, we assess whether targeting by proxy indicators is more target- and cost-efficient than the 2000/2001 Starter Pack and the 2006/2007 Agricultural Input Support Program (AISP), both of which were administered through community-based targeting systems and emphasize the main findings of the research.

The final chapter summarizes the main results of the study, comparing the model performances and emphasizing its potential contributions and implications for targeting development policies in Malawi. Further research areas and the limitations of the work are also specified.

1.5. Data Source

The present study draws mainly on the Second Malawi Integrated Household Survey (IHS2) of 2005. In 2003, the Government of Malawi decided to conduct the IHS2 in order to compare the current situation with the situation in 1997-98, and collect more detailed information in specific areas of the rural and urban sectors. The survey was conducted by the National Statistics Office (NSO) of Malawi with technical assistance from the International Food Policy Research Institute (IFPRI) and the World Bank. The IHS2 was designed to cover a wide array of subject matter whose primary objective is to provide a complete and integrated dataset to better understand the target population of households affected by poverty (NSO, 2005b).

Survey planning and pilot testing of the survey instruments took place in 2003. The survey was carried out over a period of 13 months from March 2004 through March 2005. The sampling design followed a two-stage stratified sampling selection which involved in the first stage a selection of 564 Primary Sampling Units (PSU) based on Probability Proportional to Size (PPS) sampling and in the second stage a random selection of 20 households per PSU. In total, 11280 households were surveyed. This sample is representative both at national and district levels, hence the survey provides reliable estimates for those areas.

Some specific objectives of the survey are as follows:

- provide timely and reliable information on key welfare and socioeconomic indicators and meet special data needs for the review of the Malawi Poverty Reduction Strategy which has been implemented in Malawi for the last five years since year 2002;

- provide data to come up with an update of the poverty profile for Malawi (poverty incidence, poverty gap, severity of poverty);
- derive indicators for monitoring of Malawi's progress towards achievement of the Millennium Development Goals (MDGs) and the Malawi Poverty Reduction targets (MPRs);
- provide an understanding of the living conditions of Malawi's people who live mostly in rural areas;
- provide an understanding of the linkage between poverty, agriculture, and food security and;
- provide information for the formulation of a rural development strategy.

During the IHS2 survey, information was collected at household as well as community levels on a wide range of socioeconomic characteristics, including household demography, education, health, time use and labor, security and safety, housing, consumption of food and non-food items, durable goods, agriculture, economic activities, credits, social safety nets, child anthropometry, access to basic services in the community, etc[1]. Household expenditures data were collected following the United Nations statistical system of Classification of Individual Consumption According to Purpose (COICOP). Broadly speaking, the consumption expenditures collected fall into four categories: i) food, ii) non-food and non-consumer durables, iii) consumer durable goods and, iv) actual or self-estimated rental cost of housing. The food expenditures also included the consumption from the household own production.

Since the data were collected over a period of 13 months and across different districts, there are price differences which need to be considered. In order to compare the monetary values across households, the nominal values were converted into real values using a price index that accounts for spatial and temporal price differences in the country. In addition, a national poverty line was established by the NSO. This poverty line has two components: the food poverty line and the non-food poverty line. The food poverty line or ultra poverty line

[1] See the IHS2 basic information document (NSO, 2005b) for further details on the IHS2 survey.

was derived by estimating the amount of expenditures below which an individual is unable to purchase enough food to meet its recommended daily caloric requirements of 2,400 kilocalories (kcal). The food poverty line was estimated at 27.5 Malawi Kwacha (MK) per capita per day based on a set of basket of food items.

With regard to the non-food poverty line, it was established based on those households whose consumption is close to the food poverty line, as there is no concept like calories which can be applied in that case. Households whose food expenditures per capita are five percent below or above the food poverty line were considered to calculate the kernel weighted average non-food expenditures. Based on this estimation, the non-food poverty line was set at MK16.8 per capita per day. The national total poverty line was therefore estimated at MK44.3 per capita per day (NSO, 2005c).

1.6 Targeting in the Literature

The literature on poverty targeting is well established. By definition, targeting is the process by which benefits are channeled to the members of the high priority group that a program aims to serve (Grosh and Baker, 1995). It is a means of identifying which members of society should receive a particular benefit, such as a social transfer (Rook and Freeland, 2006). It involves two elements: first defining which categories of people should be eligible to receive benefits (i.e. setting the eligibility criteria), and second establishing mechanisms for identifying those people within the population (finding out who meets the eligibility criteria). As the main target group is the poor in this research, first we define poverty, including the profile of Malawi's poor. Then, we review the poverty targeting mechanisms often used in development practice and emphasize the use of Proxy Means Tests (PMT).

1.6.1 The concept of poverty: Theoretical considerations

1.6.1.1 Defining poverty

The concept of poverty has evolved considerably since the eighteenth century. Nonetheless, poverty is defined today as a state of long-term deprivation of well-being considered adequate for a decent life (Aho et *al.*, 2003). Poverty is also seen as a long-term phenomenon which doesn't apply to individuals in temporary need. In other words, poverty is considered as a level of consumption and expenditures by individuals in a household which has been calculated to be insufficient to meet their basic needs; the benchmark being the poverty line which is the minimum level of food and non-food consumption expenditures deemed sufficient to live a decent life. This definition of poverty is absolute and essentially monetary. It favors a certain number of basic needs (e.g. food, housing, clothing, education) that must be fulfilled before an individual can be considered non-poor.

The concept of absolute poverty is standard, but nonetheless narrow view of poverty (Benson, 2002). It defines poverty independently from individual perceptions of well-being, focuses on living standards, and relies on what decision makers judge adequate from a social point of view. Likewise, it differs from Sen's conceptualization of poverty and excludes several important components of personal and household well-being, including physical security, level of participation in networks of support and affection, access to important public social infrastructure, such as health and educational services, and whether or not one can exercise ones human rights (Benson, 2002).

According to Sen (1987), poverty is a deprivation in capabilities and functionings[2]. A functioning is an achievement (e.g. being well-nourished, educated, etc.), whereas a capability is the ability to achieve (freedom to choose, longevity, fertility, etc.). Sen (1987) emphasizes that the basic needs should be formulated in line with functionings and

[2] See Sen (1987) and Johannsen (2009) for further details on Sen's capability approach.

capabilities between which exists a simultaneous and two-way relationship. "Functionings are more related to living conditions since they are different aspects of life. Capabilities, in contrast are notions of freedom, in the positive sense: what real, but also good opportunities you have regarding the life you may lead." (Sen, 1987). Even though Sen's conceptualization of poverty has received wider attention, its empirical application is challenging. Nevertheless, some attempts have been made in the literature to incorporate Sen's views in the form of poverty indices, such as the Human Development Index (HDI) and the Human Poverty Index HPI (UNDP, 1990) which are multidimensional measures of poverty and development. In sum, there is more to assessing the quality of life and the welfare of individuals than consumption and expenditures. Nonetheless, the concept of monetary poverty is widely used in economics.

Why do individuals go poor? The causes of poverty are myriad, but Aho et *al.* (2003) identify three major ones. The first refers to the unequal distribution of production factors. Countries like individuals do not have the same physical, financial, and human capital, nor do they enjoy the same access to the technological knowledge necessary for the optimal utilization of that capital. The second source of poverty stems from the choice that individuals make in allocating their time between work and leisure, spending and saving, production and consumption. According to this cause, people are responsible for their poverty because they freely choose to allocate their individual resources in certain ways and thereby assume the consequences, either positive or negative.

The third cause of poverty results from the unequal access to ways out of poverty. Therefore, improving the poor access to essential services, such as healthcare, basic education and clean water as well as access to economic opportunities, such as micro-credit and employment might help reduce poverty. Nevertheless, a country's specific context also matters in the definition of and fight against poverty.

1.6.1.2 The nature of poverty in Malawi

Malawi is a Southern African country (Figure 1) with a population of about 13.1 million people (NSO, 2008) and one of the poorest countries in the world with a per capita income of US$230 (World Bank, 2008). More than 85% of the population live in rural areas. The country is mostly agricultural with about 90% of its households working in the sector. Almost half of the households are subsistence farmers. The agricultural sector contributed about 34% to the GDP in 2007 (World Bank, 2009b) and accounted for more than 80% of export earnings (World Bank, 2009c). Malawi is a large exporter of tobacco which is the most important cash crop in the country. In 2006, tobacco production amounted to about 74% of export earnings in terms of main commodities – tobacco, tea, and sugar – (NSO, 2007).

Figure 1: Map of Malawi.
Source: Adopted from the National Statistics Office (2005a).

Deeply entrenched poverty is a major obstacle to Malawi's development and growth. As mentioned earlier, in 2005 the poverty rate was estimated at 52.4% and the ultra poverty or food poverty rate was set at 22.4% (NSO, 2005a). By international standard, this rate amounts to 61.4%[3]. Poverty is higher in rural than in urban areas (Figure 2) with the highest concentration of poor living in the Southern and Northern regions.

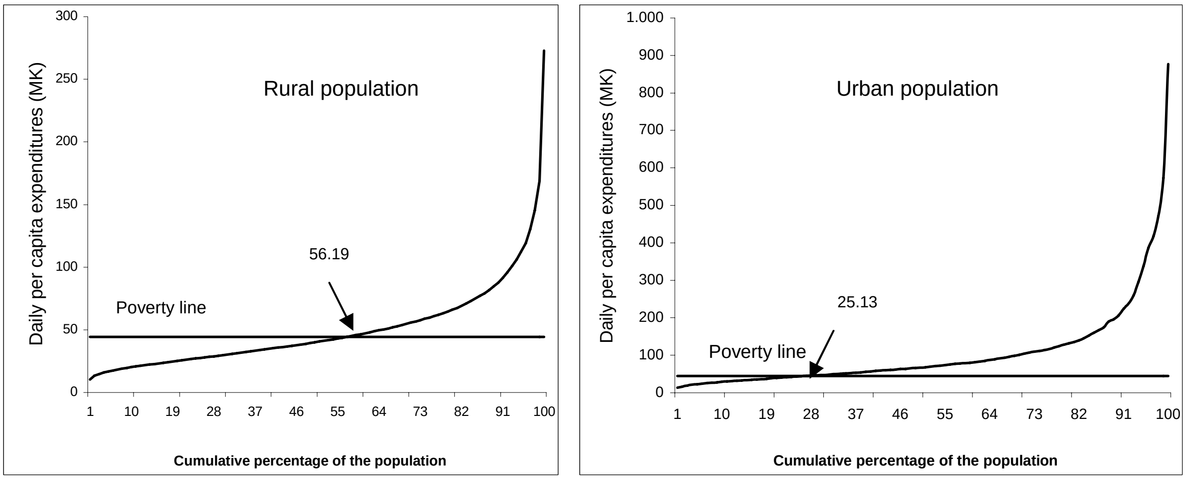

Figure 2: Welfare distribution in the Malawian population.
Source: Own results based on Malawi IHS2 data.

The curves in Figure 2 show the proportion of the population at any given daily consumption level ranked from the poorest to the richest. For example, the portions of the curves under the poverty line represent different levels of consumption of the poor. The distance between the poverty line and any point on these portions of the curves shows the consumption shortfall of the individuals. By visual inspection, these curves suggest that Malawi's poverty is deep, especially among the rural population because many of the poor are farther below the poverty line.

Likewise, Malawi has a fairly high inequality with a Gini coefficient estimated at 0.39, reflecting profound inequities in access to assets, services, and opportunities across the population (GoM and World Bank, 2007). The top third of the population has a much higher living standard than the bottom two thirds. However, inequality is substantially higher in urban than in rural areas (0.47 versus 0.34) as indicated by the Lorenz curves in Figure 3. On the other hand, the gap and severity of poverty are much lower in urban than in rural areas.

[3] This rate is estimated based on an international poverty line of US$1.25 equivalent to MK59.175 in Purchasing Power Parity.

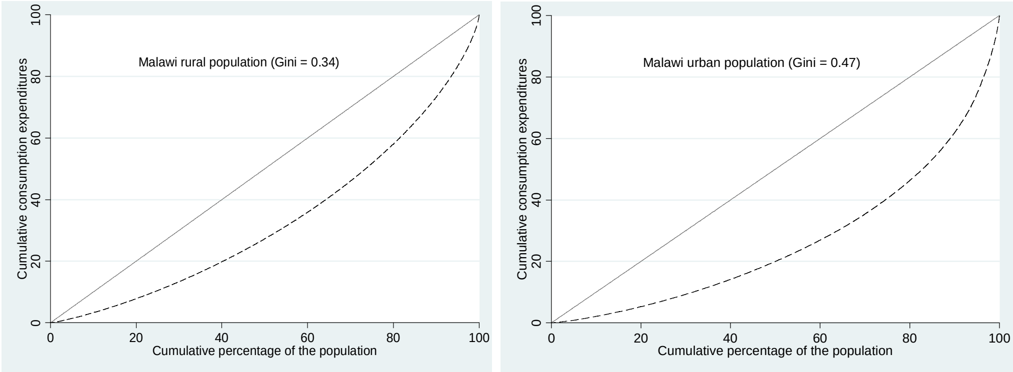

Figure 3: Lorenz curves of urban and rural Malawi.
Source: Own results based on Malawi IHS2 data.

Poverty has remained fairly stable over the last decade in the country. A recent report by the GoM and the World Bank (2007) suggests that there has been no or little progress in reducing poverty in the country since 1998. To put this in perspective, we present in Table 1 the progress in poverty between 1998 and 2005.

Table 1. Poverty in Malawi (1998 and 2005)

	1998			**2005**		
	Headcount	**Gap**	**Severity**	**Headcount**	**Gap**	**Severity**
Poor	54.1	18.6	8.5	52.4	17.8	8.0
Ultra-poor	23.6	5.7	2.0	22.4	5.3	1.8
	By region			By region		
	Poor			Poor		
Urban	18.5	4.8	1.8	25.4	7.1	2.8
Rural Overall	58.1	20.2	9.2	55.9	19.2	8.6
North	56.3	19.5	8.9	56.3	19.6	8.8
Central	47.6	14.4	6.0	46.7	14.1	5.9
South	68.4	25.7	12.3	64.4	23.8	11.2
	Ultra-poor			Ultra-poor		
Urban	4.9	1.1	0.5	7.5	1.6	0.5
Rural Overall	25.7	6.2	2.2	24.2	5.8	2.0
North	24.9	6.0	2.1	25.9	5.9	1.9
Central	16.3	3.5	3.2	16.1	3.5	1.1
South	34.6	8.9	1.2	31.5	7.9	2.8

Source: Adopted from the IHS2 report (GoM and World Bank, 2007).

As shown in Table 1, the poverty rate was estimated at 54.1% in 1998 against 52.4% in 2005, implying a reduction of less than 2%. Likewise, poverty continues to be much higher in rural than in urban areas, and the South is still the poorest regions of the country. Poverty has not been static, however. There have been some movements in relative levels of poverty. While the overall levels of poverty remain stagnant, the rankings of districts have changed. About two-third of households have moved into or out of poverty during the past decade. Such large movements reflect the fact that a quarter of Malawians have income levels within 20% of the poverty line and could therefore be forced into poverty by even slight misfortune. Urban poverty has been increasing rapidly, from 18% in 1998 to 25% in 2005. This increase has been offset by a decrease in rural poverty in the South from 68% to 64%. Similar patterns can be observed when comparing ultra-poverty as well as changes in poverty gap, severity, and inequality. These findings are also supported by recent trends in human development indicators. While there have been some improvements in education and literacy, several health indicators have worsen during the past decade (GoM and World Bank, 2007).

Who are the Malawian poor and how do they differ from the non-poor? Are some types of households more likely to be poor? Living conditions, such as housing, water, sanitation, cooking, and lighting fuel are very basic for the majority of the population, especially in rural areas, making it difficult to distinguish poor households based on these characteristics (GoM and World Bank, 2007). However, access rates are generally better in urban than in rural areas. Figure 4 provides a poverty, risk, and vulnerability profile for Malawi.

Poorer	Ultra-poverty rate: 22 percent ⇓	Poverty rate: 52 percent ⇓ Richer
Ultra-poor	**Poor**	**Transient poor/at risk**
▪ Few assets, little or no land ▪ Income less than food needs ▪ Chronic illness, female-headed, elderly-headed, high dependency ratio ▪ Low vulnerability because of low risk and low return livelihood strategy ▪ Pathway out of poverty: long term investment in human capital, utilizing existing labor and other assets	▪ Some land or labor and other assets, but vulnerable to further impoverishment ▪ Income less than food and non-food needs ▪ Heavily dependent on a single activity – usually agriculture ▪ Vulnerable to climate/weather shocks/ crop failure, chronic illness ▪ Net consumers of food ▪ Little resilience to shocks ▪ Pathway out of poverty: increase capacity to deal with shocks	▪ Land and labor assets ▪ Some resilience, but face a broad range of shocks

High dependence on single livelihood activity **Increasing diversification of livelihoods** →

Figure 4: Profile of poverty, risk and vulnerability in Malawi.
Source: Adopted from World Bank (2007).

Table 2 explores the correlation between poverty and some basic household characteristics in Malawi.

Table 2. Characterization of the Malawian poor

Dimensions	Indicators	Poor	Non-poor	T-value
Welfare	Per capita expenditures (MK)	28.79	82.27	124.33***
Demography	Household size	5.43	3.81	-39.11***
	Dependency ratio	0.54	0.38	-33.99***
	Age of household head	44.33	40.93	-11.02***
Education	Members with no schooling or incomplete primary education	1.76	0.75	-31.86***
Agriculture[1]	Total agricultural land (ha)	0.51	0.48	-0.39
	Total land cultivated (ha)	0.35	0.30	-0.93
	Number of pangas owned[2]	0.75	0.89	8.78***
	Number of hoes owned	3.02	2.87	-4.41***
	Number of sickles owned	0.78	0.72	8.45***
	Number of axes owned	0.80	0.95	3.97***

Source: Own results based on Malawi IHS2 data. ***denotes significant at 0.01 level of error
[1]Estimations based on agricultural households only. [2]Panga is a large heavy knife used for cutting the vegetation.

Apart from total agricultural and total cultivated land, the characteristics presented in Table 2 are highly correlated with poverty. Considering the household consumption, the poor consume about MK29 per capita per day against MK82 for the non-poor. Disaggregated by deciles (Figure 5), the households in the 9th and 10th deciles (richest) have an average consumption which is respectively 20 (MK196.54) and 10 (MK103.37) times higher than the consumption of the poorest households - 1st decile - (MK18.15).

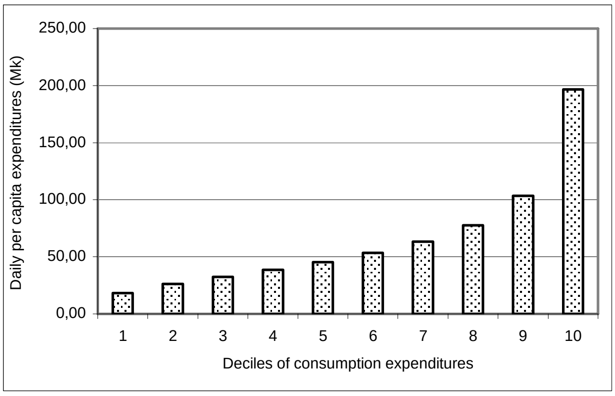

Figure 5: Household expenditures by poverty deciles.
Source: Own results based on Malawi IHS2 data.

Furthermore, Table 2 indicates that households with higher size and higher dependency ratio, and households held by older heads are more likely to be poor. For example, households in the poorest decile are more than twice as large as households in the richest decile (panel to the left of Figure 6). Likewise, household heads in the poorest decile are more than seven years older than those in the richest decile (panel to the right of Figure 6).

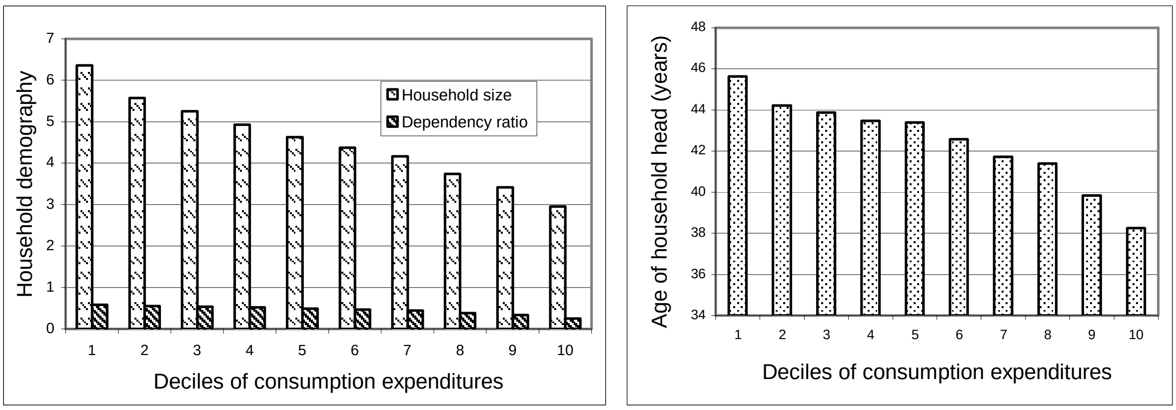

Figure 6: Household characteristics by poverty deciles.
Source: Own results based on Malawi IHS2 data.

With regard to education, Table 2 suggests that on average the illiteracy rate is higher among the poor compared to the non-poor; 1.76 versus 0.75. Likewise, the household head level of education is strongly correlated with poverty as shown in Figure 7.

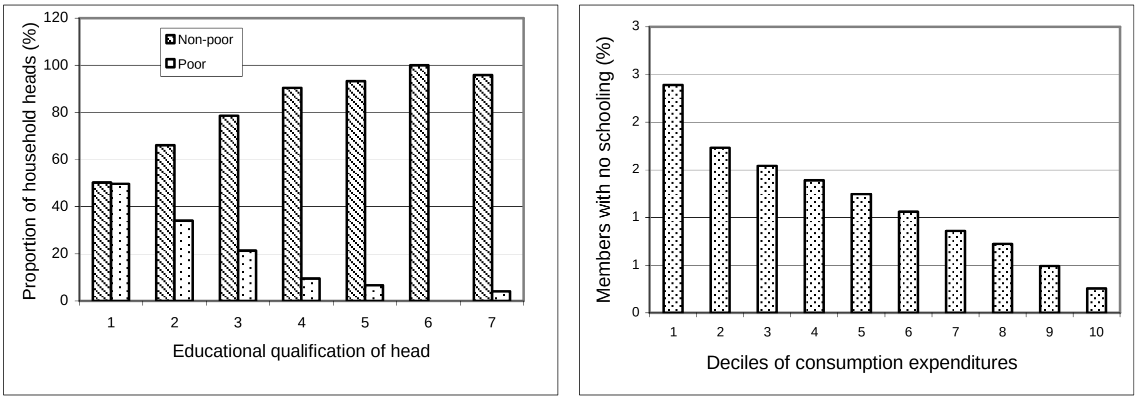

Figure 7: Household education.
Source: Own results based on Malawi IHS2 data. Educational qualification: 1=None, 2= Primary School Leaving Certificate (PSLC), 3= Junior Certificate of Education (JCE), 4= Malawi School Certificate of Education (MSCE), 5=Non-university diploma, 6=University degree, 7=Post graduate degree.

The panel to the left of Figure 7 indicates that the poverty rate decreases whereas the share of non-poor increases with increasing level of education of the household head. Higher levels of education are almost exclusively reserved to the non-poor. Likewise, the illiteracy rate decreases with increasing consumption level as shown in the panel to the right of Figure 7. Nevertheless, the absence of formal education of the head is not synonymous with poverty: some non-poor household heads do have low level of education.

With respect to the gender of the household head, the GoM and World Bank (2007) state that poverty and ultra-poverty are more common in female-headed households. About 51% of the people living in male-headed households are poor, while 59% of people living in female-headed households are poor. In addition, gender-based differences in access to resources and bargaining power reveal significant disparities in welfare between women and men (GoM and World Bank, 2007).

As concerns access to agricultural assets, such as land and equipments, the picture in Table 2 is mixed. The average land holding per capita is fairly small (0.43 ha). Holdings are higher among the poor (0.51 ha) compared to non-poor agricultural households (0.48 ha). There is, however no significant difference between poor and non-poor on average land per capita. Moreover, a visual inspection of the land distribution per decile (Figure 8) reveals no perceptible relation between holdings and poverty. Therefore, smaller landholdings are not synonymous with poverty in Malawi.

Likewise, Table 2 indicates that non-poor agricultural households own on average a higher number of pangas (0.89) and axes (0.95), whereas the poor possess a higher number of hoes (3.02) and sickles (0.78). The panel to the right of Figure 8 reveals that access to small agricultural equipments is slightly high in the richest deciles, except the number of hoes which is higher in the poorest deciles of the agricultural population.

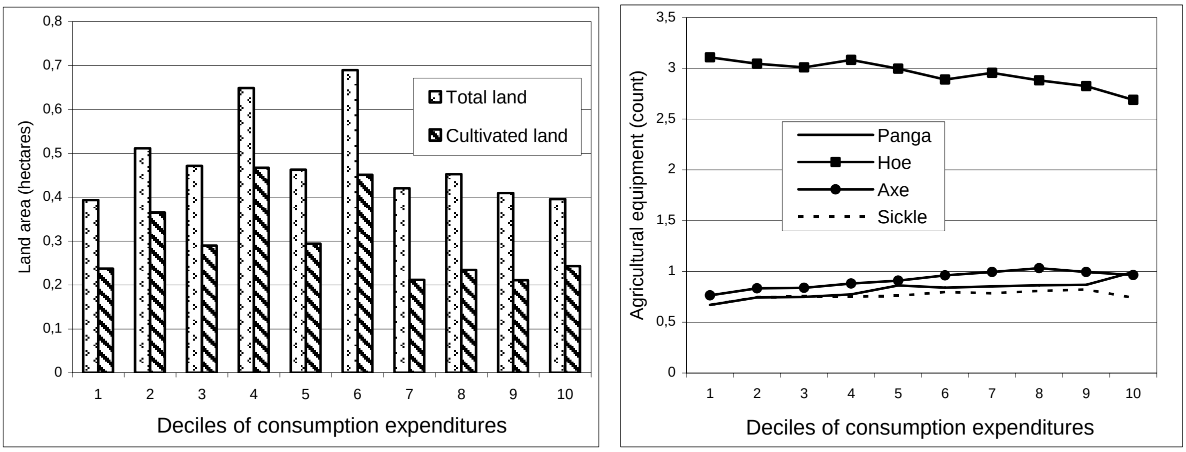

Figure 8: Household agricultural assets by poverty deciles.
Source: Own results based on Malawi IHS2 data.

According to the GoM and World Bank (2007), poor households are unable to diversify out of agriculture. Most households earn their income only from farm or fishing activity. Off-farm income sources tend to be limited to Ganyu (casual labor) for the poor. This situation reflects the lack of opportunities as a result of low levels of education, low capital base, and limited availability to credits and markets.

As mentioned earlier, housing conditions are very basic for the majority of the population. Figure 9 shows the relation between poverty and selected housing characteristics.

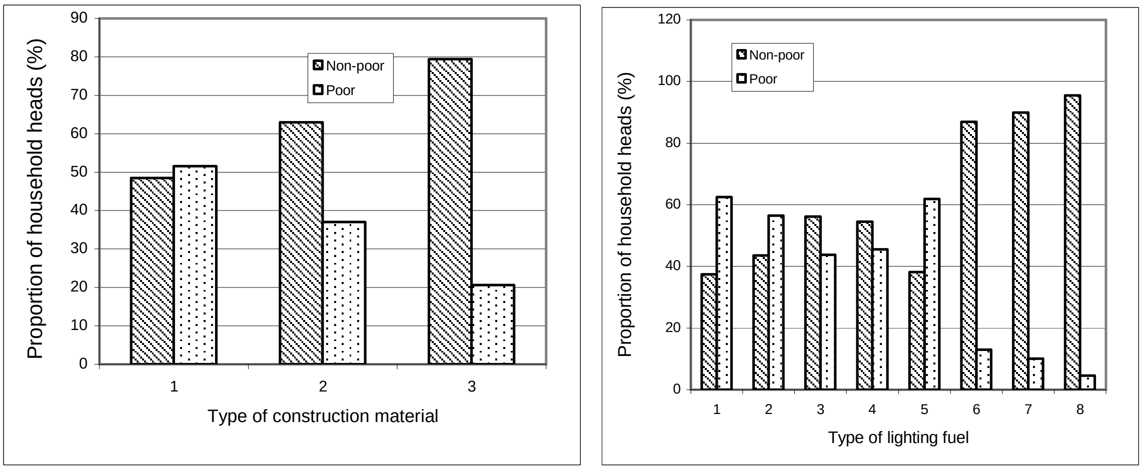

Figure 9: Household housing conditions.
Source: Own results based on Malawi IHS2 data. Type of construction material: 1=traditional, 2=semi-permanent, 3=permanent. Type of lighting fuel: 1=grass, 2=collected firewood, 3=purchased firewood, 4=paraffin, 5=gas, 6=candles, 7=battery/dry cell, 8=electricity.

The panel to the left of Figure 9 indicates a likely correlation between poverty and housing; the majority of households living in houses built with traditional materials are poor, whereas those living in houses with semi-permanent and permanent structures are overwhelmingly non-poor. For instance, more than 50% of the households living in traditional structures are poor, whereas more than 80% of the households living in permanent structures are non-poor.

Concerning the type of lighting fuel, the panel to the right of Figure 9 shows that the poverty rate decreases with increasing lighting quality. For example, more than 60% of the households using grass as lighting fuel are poor. On the other hand, over 80% of the households using candles, battery, or electricity as lighting fuel are non-poor and less than 20% of them are poor. The same trend applies to the house floor and wall material in appendix 8. Therefore, it seems fair to say that the poor tend to live in very poor housing conditions compared to non-poor in Malawi.

The GoM and World Bank (2007) report that limited access to markets, financial services, key transport infrastructure, and remoteness are the main obstacles to getting out of poverty. The latter also emphasize that the existence of widespread risk and the frequent occurrence of shocks, such as illness, death, crop failure, livestock disease, and falls in crop prices, is a major cause of poverty in the country.

The description of Malawi's poor can guide the development of effective poverty reduction policies and programs. However, reducing poverty requires first identifying the poor. How to identify and target those who are unable to meet their basic needs? We discuss the issue in the following section.

1.6.2 Targeting the poor: Empirical methods

Targeting methods have all the same goal – to correctly identify which households or individuals should receive benefits based on predefined criteria (e.g. individuals living below the poverty line, vulnerable households, etc.) and which should not. Targeting can be based on different units, such as households or individuals. And the targeted beneficiary is not necessarily the same as the recipient (Rook and Freeland, 2006); for example a child support grant targeted at under-14s would not be given directly to the child, but to the head of the child's household.

In practice, a number of methods are used to target development interventions at the poor. The main targeting methods include means tests, proxy means tests, geographical targeting, categorical targeting, community-based targeting, and self-targeting. In the absence of targeting, program benefits are provided "universally" – In other words to everyone in the population. Table 3 gives an overview of existing targeting methods, including their advantages and weaknesses.

Table 3 is self-explanatory. A few remarks can be drawn from the Table. None of the targeting methods is perfect; all of them have advantages but also some limitations. Likewise, they are not mutually exclusive and may work better in combination if feasible. The appropriateness of targeting is determined by its costs. Divergent views on the efficacy of targeted interventions are based on differing assessments of three questions (Coady et *al.*, 2004). "Are the methods used for reaching the poor likely to achieve better targeting outcomes? Are they cost-effective? Do they raise the living standards of the poor?" Targeting is not costless. There is a whole range of costs associated with narrow targeting: administrative costs, incentive effects, private costs borne by beneficiaries, stigmatization and social discrimination, and political costs. On the other hand, universal regimes are prohibitive because of excessive leakage to the non-poor and budget constraint. Because of the special relevance of Proxy Means Tests (PMTs) for this research, we provide in the following section further details on the tests.

Table 3. Overview of poverty targeting methods

Characteristics / Targeting methods	Definitions	Advantages	Disadvantages	Applications
Verified means tests	Aimed at the poor, based on the measurement of the beneficiary income, assets and/or nutrition status	Best way of determining eligibility, focus on the poor, reduces inclusion errors	Very costly and difficult to administer, require regular and frequent monitoring, administrative compliance results in inclusion errors, possible stigma, performance rise with country-income level, appropriate for countries with higher administrative capacity and well documented economic transactions, and programs that provide large benefits	Child support grant (South Africa), GAPVU (Mozambique)
Simple means tests	Rely on self-reported income or welfare status or qualitative assessment of a social worker with no independent verification	Simple, quick, and easy	Inaccurate, introduce perverse incentives to lie, especially when no triangulating information is collected	1980 Food Stamp Program (Jamaica)
Proxy means tests	Aimed at the poor, based more easily observable "proxy" measures of poverty (e.g. location, housing, assets) or vulnerability (e.g. household characteristics)	Focus on the poor and vulnerable, reduces inclusion and exclusion errors, can be easily replicated, fairly accurate, can guaranty horizontal equity, fairly simple training required, can be used to evaluate program outreach and impacts, system can be shared between different programs	Difficult to construct valid and accurate proxy indicators, may introduce perverse incentives to meet proxy criteria, effective verification process may be needed, may be costly and difficult to administer, especially at scale, rigid, static, possible stigma	BEAM (Zimbabwe), PAM (Zambia), INAS (Mozambique), FICHAS (Chile), PROGRESA (Mexico)
Community-based targeting	Aimed at the poor, based on community perception of poverty and vulnerability	Reflects and values local knowledge and understanding of poverty and vulnerability, simple, low administrative costs, can work in a well defined community with good social consensus	Significant inclusion and exclusion errors, may perpetuate local patronage structures and gender bias, can be divisive, difficult to evaluate, not replicable, accuracy cannot be verified, communities often tend to modify criteria to suit their interests, diverging interests of community members, notion of community is problematic	Kalomo cash transfer (Zambia), Mchindji cash transfer (Malawi), Dowa emergency cash transfer, Starter Pack, AISP (Malawi)

Source: Own conception and compilations from Rook and Freeland (2006), Coady et *al.* (2002), and Hoddinot (1999).
GAPVU: Gabinete de Apoio à População Vulnerável. BEAM: Basic Education Assistance Module. PAM: Program Against Malnutrition. AISP: Agricultural Input Support Program. INAS: National Institute for Social Welfare. PROGRESA: Programa de Educacion, Salud y Alimentacion.

Table 3. Overview of poverty targeting methods (continued)

Characteristics / Targeting methods	Definitions	Advantages	Disadvantages	Applications
Categorical/demographic targeting	Aimed at specific identifiable categories of the population associated with poverty (e.g. elders, children, female-headed households, disabled, orphans)	Easy to administer, objective/ transparent measure, high level of public support, suitable when correlation between poverty and group characteristics is strong, lower administrative costs compared to other methods	Inclusion and exclusion errors, does not necessarily target the poor and most people in need, documentation and administrative constraints may increase transaction costs for the beneficiaries	Old age pension (Lesotho), Child support grant (South Africa), Disability pension (Namibia)
Geographical targeting	Aimed at specific geographic areas with disproportionate number of poor, rarely used alone to target the poor	Easy to administer, useful as a first level targeting approach, may be more cost-efficient to concentrate resources in areas with disproportionate number of poor, can be used by all countries, useful for crisis situation and immediate needs	Inclusion and exclusion errors, can encourage migration, does not say how much resources to give to which areas, may be politically unfeasible, violate the principles of horizontal equity, leave out poor living in richer regions	Chipata cash transfer (Zambia), Social Investment Fund (Bolivia), Food subsidy (Egypt), Food-for-Education (Bangladesh)
Self-targeting[4]	Open to all, but offering benefits to which only the poor will be attracted (e.g. low wage rate), focuses on the quality of the good provided	Low administrative costs, can be linked to skill development and income generation, can generate improved infrastructure (e.g. public works), appropriate for transitory poverty, where poor and non-poor have different consumption and wage patterns	High exclusion errors, potential bias against women, those who cannot do hard physical work, can ensure good targeting but may limit the level of benefit, opportunity costs of participation, stigma, may be difficult to find a commodity that is consumed only by the poor, or not used in the livestock industry, or a wage rate that attracts only the poor, can be complex to design and administer.	MASAF public works (Malawi), Zibambele program (South Africa), EGS Maharashtra (India)
Market-delivered	Provided to all through market mechanisms (subsidies, price support)	Easy to administer	Costly and inefficient, highly regressive, excludes those who are outside the market (e.g. the poor, etc.), may distort market	Fertilizer subsidy (Malawi), price subsidies
Universal targeting	Provided unconditionally to all	Reduces costs of targeting, no exclusion errors, high level of pubic support, respects rights	High inclusion errors, too costly, cannot be sustained, especially in poor countries, low level of impacts	Basic income grant (South Africa, Namibia)

Source: Own conception plus compilations from Rook and Freeland (2006), Coady et *al.* (2002), and Hoddinot (1999).
MASAF: Malawi Social Action Fund. EGS: Employment Guarantee Scheme.

[4] Strictly speaking, all targeting methods are to some extent self-targeted because targeting always implies some actions and therefore costs for the beneficiaries in order to qualify for the program (Coady et *al.*, 2002).

1.6.3. Proxy means tests in the literature

Because of the difficulties and the costs associated with collecting and verifying detailed information on household income or consumption, especially in developing countries, governments and development institutions rely on alternative targeting methods. On such method is proxy means test.

Proxy means tests use household socioeconomic indicators to proxy its income or welfare level. As in any targeting method, the aim is to find a few indicators that are less costly to identify, but are sufficiently correlated with household income or expenditures to be used for poverty alleviation (Besley and Kanbur, 1993). These indicators are used to calculate a score that indicates how well off the household is. This score is then used to determine household eligibility to development or safety net programs (consumption and production subsidies, free food, education, health, etc.), and possibly the level of benefits. The system can also potentially be used for assessing the welfare impacts of agricultural development projects as argued by Van Bastelaer and Zeller (2006).

The first step in designing a proxy means test is to select a few variables that are well correlated with poverty and have three characteristics (Coady et *al.*, 2002): i) the variables should be few enough that it is feasible to apply the proxy means tests to a significant share of the population that may apply for the program, maybe as much as a third; ii) the variables selected must be easy to measure or observe (see for example Johannsen, 2009; Houssou et *al.*, 2007; Zeller et *al.*, 2006b; Zeller et *al.*, 2005a, b; Zeller and Alcaraz V., 2005a, b); and iii) they should be relatively difficult for the households to manipulate just to get into the program. These variables are usually available in national household surveys and Living Standard Measurement Surveys (LSMS). They often include different dimensions of poverty, such as housing, location, assets, demography, occupation, etc.

Once the variables have been chosen, statistical methods are used to associate a weight with each variable. One common approach is regression analyses, such as Ordinary Least Square (OLS), Linear Probability Model (LPM), Logit or Probit, and Quantile regressions which are used to regress household welfare measured by income or consumption on the selected variables. This procedure is often iterative in that the variables initially selected are chosen on the basis of a more comprehensive statistical analysis that evaluates their predictive power, i.e. how closely they are correlated with household welfare. Additionally, out-of-sample validations (across time and or space) are conducted when feasible, to gauge how well the system is likely to perform on the field. These tests involve the use of non-overlapping samples derived from the initial dataset or the use of datasets from different time periods to assess the predictive ability of the system (see for example Johannsen, 2009; Houssou et *al.*, 2007; Benson et *al.*, 2006; Narayam and Yoshida, 2005). Sometimes, the weights are rounded to simplify the system and facilitate calculation of scores on the field.

A key feature of proxy means test is the formulaic nature of its calculation of need. The test has the merit of making replicable judgments using consistent and visible criteria (Coady et *al.*, 2002). Proxy means tests are highly accurate and less prone to criticism of politicization or randomness. They are also less costly than verified means tests. Likewise, they are appropriate for large and long term programs, but less so for crisis situation (e.g. emergency food relief as a result of severe drought). Furthermore, the estimation methods used to develop proxy means test systems may require a high level of technological skills and may not always be well understood, especially by non-specialists. Depending on the nature of the indicators used, proxy means tests can capture only chronic or transient poverty or both.

Additional methods used to develop proxy means test models include principal component and discriminant analyses which measure relative poverty. However, a relative welfare measure only identifies the poor, but doesn't account for how much poor there are;

focusing on who get program benefits, but not how much they get. Such index-based measures of poverty are useful when income or expenditures data are not available.

The efficacy of proxy means testing is demonstrated in various studies, such as Coady and Parker (2009), Johannsen (2009), Houssou et *al.* (2007), Schreiner (2006), Benson et *al.* (2006), Zeller et *al.* (2006), Narayam and Yoshida (2005), Zeller et *al.* (2005a, b), Zeller and Alcaraz V. (2005a, b), Coady et *al.* (2004), Ahmed and Bouis (2002), Baulch (2002), Braithwaite et *al.* (1999), Grosh and Baker (1995), Grosh (1994), and Glewwe and Kanaan (1989). While there is bound to be some leakage, no indicator being perfectly correlated with welfare, it is hoped that any leakage of benefits to those who are not poor is much less expensive than administering a means test or providing benefits universally to the population.

Targeting can work, but not always. In a comprehensive survey of 122 targeted antipoverty interventions, Coady et *al.* (2004) found that differences in country characteristics and implementation mechanisms are important determinants of program effectiveness than the choice of targeting method per se. For example, administrative arrangements associated with collecting and verifying information are vital to ensuring low errors of exclusion of the poor and low leakage to the non-poor. No matter how well or badly the statistical formula works, if the poor don't register for the program, it will have high exclusion errors (Coady et *al.*, 2002).

There is a long tradition of targeting by proxy means tests in Latin America. Social safety nets have long relied on proxy means tests to provide benefits to the poor (e.g. Chile's Ficha CAS, Columbia's SISBEN, and Mexico's PROGRESA). Likewise, in 2000 the U.S. Congress passed the Microenterprise for Self-Reliance and International Anti-Corruption Act which emphasized that half of all United States Agency for International Development (USAID) microenterprise funds benefit the very-poor. To meet this target, a subsequent legislation required USAID to develop and certify low cost proxy means tests tools for assessing the poverty status of microenterprise clients. Within this framework, proxy means tests are now being developed and field-tested in many developing countries.

In general, to evaluate the performances of a proxy means targeting system, a two-by-two cross-table of the actual versus predicted poverty status is used. The actual poverty status is determined by comparing the household actual expenditures to the poverty line. Households with expenditures below the poverty line are classified as poor, otherwise they are deemed non-poor. Likewise, the predicted household poverty status is determined by comparing the predictions (e.g. predicted expenditures or probability of being poor) to a benchmark (e.g. poverty line or predefined cut-off) after estimation. Table 4 illustrates the cross-classifications.

Table 4. Actual vs. predicted household poverty status

Actual poverty status	**Predicted poverty status**		
	Non-poor	**Poor**	**Total**
Non-Poor	444	104	548
Poor	105	146	251
Total	549	250	799

Source: Adapted from Zeller et *al.* (2006b).

Table 4 crosses the predicted versus the actual household poverty status. The results indicate that out of 548 actually non-poor households, 444 are correctly predicted as non-poor, whereas 104 are wrongly predicted as poor. Likewise, 146 of 251 truly poor households are correctly predicted as poor, whereas 105 are wrongly predicted as non-poor. Based on the above results, different performances measures are used to assess the accuracy of the system as presented in Table 5.

Table 5. Indicators of targeting performances

Accuracy ratios	Definitions
Total Accuracy	Percentage of the total sample households whose poverty status is correctly predicted by the estimation method.
Poverty Accuracy	Number of households correctly predicted as poor, expressed as a percentage of the total number of poor.
Non-Poverty Accuracy	Number of households correctly predicted as non-poor, expressed as percentage of the total number of non-poor.
Undercoverage	Number of poor households predicted as non-poor, expressed as a percentage of the total number of poor.
Leakage	Number of non-poor households predicted as poor, expressed as a percentage of the total number of poor.
Poverty Incidence Error (PIE)	Difference between predicted and actual poverty incidence, measured in percentage points.
Balanced Poverty Accuracy Criterion (BPAC)	Poverty accuracy minus the absolute difference between undercoverage and leakage, measured in percentage points.

Source: IRIS (2005).

The first three measures in Table 5 are self-explanatory. Undercoverage and leakage are exclusion and inclusion errors, respectively. They are extensively used to assess the targeting efficiency of development policies (Valdivia, 2005; Ahmed et *al.*, 2004; Weiss, 2004). In statistical terminology, undercoverage is also known as type II error or *false negative* and leakage is termed as type I error or *false positive*.

The performance measure PIE indicates the precision of a model in correctly predicting the observed poverty rate. Positive PIE values indicate an overestimation of the poverty incidence, whereas negative values show the opposite. The Balanced Poverty Acurracy Criterion (BPAC) considers three accuracy measures that are especially relevant for poverty targeting: poverty accuracy, leakage, and undercoverage. These three measures exhibit trade-offs. For example, minimizing leakage leads to higher undercoverage and lower poverty accuracy. Higher positive values for BPAC indicate higher poverty accuracy, adjusted by the absolute difference between leakage and undercoverage.

Using the results in Table 4 and the indicators in Table 5, the performances of the system can be calculated as follows:

- Total Accuracy = ((444 + 146) / 799)* 100 = 73.84%;
- Poverty Accuracy = (146 / 251)* 100 = 58.18%;
- Non-Poverty Accuracy = (444 / 548)* 100 = 81.02%;
- Undercoverage = (105 / 251)* 100 = 41.83%;
- Leakage = (104 / 251)* 100 = 41.43%;
- PIE = 31.29-31.41= -0.13 percentage points;
- BPAC = 58.18-abs(41.83-41.43) = 57.77 percentage points.

In general, actions to reduce undercoverage (e.g. raising the cut-off point) may increase the leakage rate and vice versa. Table 6 reviews the performances of selected studies (as measured by their undercoverage and leakage rates) on proxy means tests in different countries.

Table 6. Selected studies on proxy means tests

Results / **Studies**	**Poverty rate** (%)	**Estimation methods**	**Number of indicators**	**Out-of-sample tests**	**Performances**	
					Under-coverage	**Leakage**
Iris (2008)[1] Malawi	61.4	Iterative quantile	15	Yes	16.55	17.09
Johannsen (2007) Peru	54	Weighted OLS	10	Yes	20	25.6
Houssou et *al.* (2009)[2] Uganda	32.36	Probit	10	Yes	47.06	43.53
Schreiner (2006) India	46.37	Logit	15	No	38.5	16.1
Benson et *al.* (2006)						
Rural Malawi	54.8	OLS	17	Yes	27	34
Urban Malawi	51.6	OLS	09	Yes	18.5	25.4
Zeller et *al.* (2006b) Bangladesh	31.41	Principal component	13	No	41.83	41.43
Zeller et *al.* (2005a) Bangladesh	31.41	Iterative quantile	15	No	30.28	30.28
Zeller & Alcaraz V. (2005a) Uganda	31.4	Iterative quantile	15	No	38.04	37.65
Zeller & Alcaraz V. (2005b) Kazakstan	4.52	Iterative quantile	15	No	54.05	62.16
Zeller et *al.* (2005b) Peru	26.88	Iterative quantile	15	No	27.44	27.91

Source: Compiled from the literature. [1]Preliminary results. [2] Results based on 0.5 cut-off probability.

Table 6. Selected studies on proxy means tests (continued)

Studies \ Results	Poverty rate (%)	Estimation methods	Number of indicators	Out-of-sample tests	Performances	
					Under-coverage	Leakage
Narayan &Yoshida (2005) Sri Lanka	40	OLS	34	Yes	28	31
Ahmed & Bouis (2002) Egypt	36.5	OLS	09	No	28.2	16.3
Baulch (2002)[2] Rural Vietnam	45.5	Stepwise probit	09	No	26.9	21.7
Urban Vietnam	9.2	Stepwise probit	06	No	53.3	1.9
Grosh & Baker (1995) Jamaica	30	OLS	25	No	41	34.2

Source: Compiled from the literature. [1]Preliminary results. [2] Results based on 0.5 cut-off probability.

As shown in Table 6, a number of studies have applied proxy means tests for targeting the poor in the past. Using an iterative Quantile regression with 15 indicator set in Bangladesh, Zeller et *al.* (2005a) achieve an undercoverage and leakage of about 30%. Likewise, using the OLS and a set of nine indicators for targeting food subsidies in Egypt, Ahmed and Bouis (2002) obtain an undercoverage of 28% and a leakage of 16%. However, none of the above authors validates the targeting performances out-of-sample to assess the robustness of their results; they used the same sample to fit the models and estimate the predictions.

Conversely, Narayan and Yoshida (2005) conduct out-of-sample tests based on 34 indicator set in Sri Lanka. Their results yield an undercoverage of 28% and a leakage of 31%. Similarly, Benson et *al.* (2006) achieve an undercoverage of 27% and a leakage of 34% in Rural Malawi. Differences in the number and type of variables (categorical or continuous), their practicality, the poverty rate (or poverty line applied), the estimation methods, and whether the models are validated out-of-sample or not, make difficult a systematic comparison of targeting performances across studies. Nonetheless, the general trend is that none of the studies identifies perfectly the poor. They all exhibit some targeting errors.

1.6.4 Malawi's targeted programs: Costs and targeting efficiency

Historically, there has been no coherent strategy for targeting the poor and vulnerable in Malawi (Smith, 2001). There exist a large number of targeted programs in the country, most of which are uncoordinated short-term relief or emergency responses. In the period 2003-2006, including emergency aid and disaster response, the combined safety nets/social protection system amounted to an average of more than US$134 million per year; that is about 6.5% of the country's GDP (World Bank, 2007). The main programs implemented in the past included the Public Work Program (PWP), the Food-for-Work Program (FWP), the subsidized/free food distribution, such as food transfers and school feeding and the subsidized agricultural inputs, such as fertilizer and seeds (input subsidies and transfers). Table 7 describes the programs implemented in Malawi between 2003 and 2006.

Table 7. Malawi's targeted programs from 2003 to 2006

Programs	**Number of projects**	**Costs** (US$ million)	**Number of beneficiaries**	**Average cost/ beneficiary** (MK)
Cash-for-work	8	212.5	863,328	34213.53
Food transfers	2	128.0	199,550	89160.61
Input subsidies	1	60.0	2,000,000	4170.00
Input transfers	2	49.5	3,701,350	1858.92
Input-for-work	3	27.4	238,857	15945.11
School feeding	3	31.0	610,000	7063.93
Supplementary feeding	2	11.1	64,208	24029.72
Food-for-work	3	10.1	92,293	15211.34
Relief transfers	1	0.9	1,225	102122.45
Food and cash	1	0.6	5,050	16514.85
Cash transfers	2	0.5	7,065	9837.23

Source: Adapted from the World Bank (2007). Average cost based on an exchange rate of US$1=MK139.

The cash-for-work was one of the largest programs under the PWP. It was self-targeted and provided transfers to the poor on the basis of a low wage rate and was operated by the Malawi Social Action Fund (MASAF). The program was launched in 2005 as an emergency response to a national food shortage that occurred in the country following the 2004/2005 drought. The underlying principle of the program is that it should self-select the poor, by paying less than the prevailing market wage. This ensures that the non-poor will not be attracted. It also increases the probability of employing women as informal wage rates for women are generally below those for men. However, the program has been plagued by design challenges, one of which was getting the wage rate right (Smith, 2001).

The main Food-for-work paid participants a given amount of maize, using food aid provided by the World Food Program. Like the PWP, it is self-targeted on the basis of a work requirement and a relatively low wage rate. Its major advantage is that food payments are selective of women than are cash. The drawback is that logistics of moving food around the country, and of paying in food is cumbersome and expensive. As a result, coverage has generally been lower than was intended.

Input transfers and subsidies are the most extensive programs. They aim at raising household food self-sufficiency and maintaining total national level of food production. Fertilizer subsidy has been a key element of the Malawian Government present policy (World Bank, 2007). The provision of agricultural inputs, especially fertilizer enjoys a special place in the popular hierarchy of anti-poverty measures in the country (Smith, 2001). For example, the Starter Pack Initiative (SPI) of 1998/1999 provided 10 kilograms (kg) of fertilizer along with seed to all farmers at a cost of US$27 million. One of the major drawbacks of the program is that it was universal. Universality of course eases the administrative burden and ensures wide popular and political support, but confronted with the fiscal burden, the Government subsequently scaled down the program to a targeted version. Funding has, therefore been substantially reduced to about US$11 million in 2000/01. In 2005/2006 growing season, a new fertilizer subsidy program was devised in the country as a result of an extremely poor harvest in 2004/2005. The program was extended and scaled up in the following year. Both programs cost in total US$124 million (Ricker-Gilbert and Jayne, 2009).

In addition to the above-mentioned programs, there have been large scale food distribution programs in the past. These programs included the School Feeding and Supplementary Feeding Programs. The main problem with the school feeding is that the program is expensive and it is not selective of the poor as it is untargeted within schools. Furthermore, there is no reason to believe that the poor are more likely to be represented in schools than among the population as a whole (Smith, 2001).

With regard to the targeting mechanisms, most of previous programs were administered through different methods, including universal provision, geographical targeting, self-targeting, and mainly community-based targeting. But, they display a poor targeting efficiency and some of them are too costly to sustain (e.g. programs based on universal provision of benefits). Likewise, the targeting mechanisms applied are not replicable and their cost-effectiveness and poverty impacts are rarely investigated. Almost all these interventions have targeting problems (GoM and World Bank, 2007). To put this in perspective, we plot in Figure 10 the percentage of households that reported benefiting from various programs by poverty deciles.

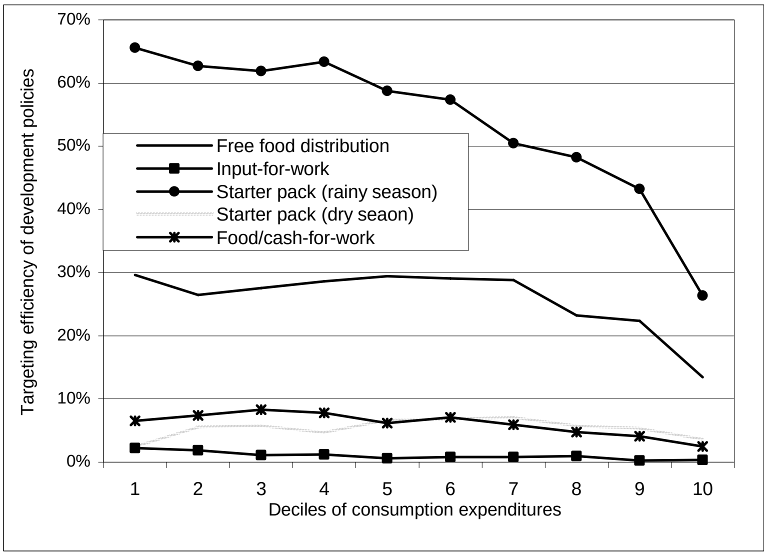

Figure 10: Targeting efficiency of Malawi's development programs.
Source: Own results based on Malawi IHS2 data.

Figure 10 shows that in general, the coverage of program beneficiaries decreases with increasing consumption. This indicates that past programs were somehow progressive.

Likewise, the graph illustrates the tradeoff between undercoverage and leakage: the higher the coverage of the poorest deciles, the higher the program leakage, i.e. the coverage of the richest deciles. Apart from the *Starter Pack* (rainy season) which covered about 60% to 70% of the first five deciles, very few households in the poorest deciles benefited from most interventions. For example, about 30% of households in the poorest decile reported benefiting from the *Free food distribution program*. At the same time, all of the programs wrongly covered the richest deciles. Further results confirm the same pattern (appendix 9).

1.7 Summary

This introductory chapter has stated the problematic of poverty and the challenge of targeting Malawi's poor and smallholder farmers. It has appeared that much more remains to be done or corrected as the Government of Malawi reflects on improving the targeting of future interventions. The literature review suggests that none of the available methods is perfect at targeting poverty. Similarly, the description of Malawi's poverty profile has shed some light on the definition of the poor and their distinctive characteristics relative to the non-poor in the country.

Furthermore, the assessment of past interventions suggests that previous programs have been badly targeted at the poor in the country. However, targeting errors can be reduced if more accurate targeting methods are used and programs are rationalized and properly implemented. The extent to which the poor and smallholder farmers are accurately targeted will determine the success of future actions for reducing the country's pervasive poverty.

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CHAPTER II

OPERATIONAL MODELS FOR IMPROVING THE TARGETING EFFICIENCY OF DEVELOPMENT POLICIES

A systematic comparison of different estimation methods using out-of-sample tests

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Abstract

Accurate targeting is key for the success of any development policy. While a number of factors might explain low targeting efficiency, such as governance failure, political interference, or lack of political will, this paper focuses on improving indicator-based models that identify poor households and smallholder farmers more accurately.

Using stepwise regressions along with out-of-sample validation tests and receiver operating characteristic curves, this paper develops proxy means test models for rural and urban Malawi. The models developed have proven their validity in an independent sample and therefore, can be used to target a wide range of development policies at the poor. This makes the models potentially interesting policy tools for the country.

Keywords: *Malawi, poverty targeting, predictions, proxy means tests, out-of-sample tests, ROC curve, bootstrap.*

1. Introduction

Malawi is a very poor and mostly agricultural country. According to the Second Integrated Household Survey (IHS2), 52.4% of Malawians are poor and about 90% of the population live in rural areas (National Statistics Office - NSO -, 2005a). Likewise, most of the rural population depends on agriculture for their livelihoods.

In response to widespread poverty and endemic food insecurity in the country, the Government of Malawi enacted different programs, such as credit, fertilizer, improved seed, and conditional cash transfer through community-based and self-targeting mechanisms. However, most of these programs were not efficiently targeted at the poor and smallholder farmers. Existing statistics indicate that the problem of food insecurity remains rampant (Chinsinga, 2005). Almost all social protection programs are poorly targeted in the country.

As a result, poverty and food insecurity have not been reduced in the country. Recent estimates suggest that the poverty rate has declined less than 2% over a decade (Government of Malawi and World Bank, 2007). It has therefore appeared that much more needs to be done to develop a low cost, fairly accurate, and easy system to target the poorest (PMS, 2000). Such an operational system is also useful for assessing whether a project, policy or development institution reaches the poor and smallholder farmers.

This paper addresses these challenges. We develop proxy means test models for targeting Malawi's poor and smallholder farmers. Proxy means tests use household socioeconomic indicators to proxy household poverty or welfare level. These tests have the merit of making replicable judgments using consistent and visible criteria (Coady et *al.*, 2002). They are also simple to implement and less costly than sophisticated means tests[5].

In addition to the Weighted Least Square (WLS) estimation method, we apply the Weighted Logit (WL) regression with stepwise selection to identify the best set of indicators

[5] See Coady et *al.* (2002) and Grosh and Baker (1995) for further details on means tests.

for correctly predicting the household poverty status. Furthermore, we compare the predictive power and the robustness of both estimation methods using out-of-sample tests and Receiver Operating Characteristic (ROC) curves. Finally, we estimate the prediction intervals of model performance measures using the bootstrap algorithm. The set of indicators used in our models include objective and easily verifiable variables. These variables are usually available in Living Standard Measurement Surveys (LSMS) data and most household surveys in developing countries.

This paper is organized as follows. Section 2 sets out the methodology, whereas section 3 presents the results with applications to household data from Malawi. Section 4 ends the work with some concluding remarks.

2. Data and Methodology

2.1 Data

This research used the Second Malawi Integrated Household Survey (IHS2) data. The National Statistics Office of Malawi conducted the IHS2 with the assistance of the International Food Policy Research Institute (IFPRI) and the World Bank (NSO, 2005b)[6]. The IHS2 was carried out from March 2004 through March 2005 and covered a nationally representative sample of 11,280 households that were selected based on a two-stage stratified sampling design. This design involved in the first stage the selection of the Primary Sampling Units (PSU) based on Probability Proportional to Size (PPS) sampling and in the second stage, a random selection of 20 households per PSU.

Compared to previous experiences, this survey is particularly appropriate for the research for three main reasons. First, it used an improved methodology for collecting and computing household consumption expenditures. Second, the survey covered a wide range of

[6] We gratefully acknowledge the National Statistics Office of Malawi for providing us with the data.

poverty indicators that are potentially suitable to developing proxy means test models. Third, the sample is representative at national as well as district levels.

Poverty in this research is defined as a level of consumption and expenditures by individuals in a household which has been calculated to be insufficient to meet their basic needs. It is generally agreed among analysts that expenditures (as an income proxy) are a more robust measure of poverty than income itself (Deaton, 1997). This definition is a standard, but nonetheless narrow view of poverty (Benson, 2002). Its excludes several important components of personal and household well-being, including physical security, level of participation in networks of support and affection, access to important public social infrastructure, such as health and educational services, and whether or not one can exercise ones human rights. In sum, there is more to assessing the quality of life and the welfare of individuals than consumption and expenditure. In view of the widespread use of monetary poverty lines with expenditure-based measures of poverty however, the research pursues a policy-relevant objective by identifying indicator-based tools that can simplify the identification of rural poor and measure welfare changes over time in poor populations.

2.2 Model estimation methods

2.2.1 Poverty predictors and sample selection

The set of poverty predictors includes 148 practical indicators selected from a pool of 800 potential variables to ensure an operational use of the tools[7]. The practicality refers to two criteria: *difficulty and verifiability of indicators.* Initially, variables that are difficult to measure, verify (for example, subjective variables), and compute were excluded from the set of available variables. Before estimating the regressions, the list of selected variables was further screened

[7] The list of indicators was reduced to 112 for the urban model; some of the variables were not relevant in urban areas.

for multicollinearity within dimension[8]. This screening of potential poverty predictors is the first step toward the selection of indicators that are significantly associated with poverty.

Separate models were estimated for rural and urban households because of substantial differences between both areas. In order to perform the validation tests, each sample was first split into two sub-samples following the ratio 67:33. The larger sample or *calibration sample* was employed to estimate the model i.e. identify the best set of variables and their weights, whereas the smaller sample or *validation sample* was used to test out-of-sample the predictive accuracy of the model. In the out-of-sample tests, we therefore applied the set of identified indicators and their derived weights to predict the household poverty status. In order to mimic the initial sample selection, we followed in the sample split followed a two-stage stratified sampling design. This design ensures that all strata are adequately represented in the calibration samples. A simple random sampling split would not guaranty such representativity.

With the 67:33 split and the stratified sampling design, we put more emphasis on the model calibration than validation. Furthermore, the continued representativity of the calibration samples was assessed by testing the differences in estimates between the samples and the full datasets. The results of the tests show that there is no statistically significant difference between both sets. Therefore, the calibration samples are as representative as the full datasets.

After performing the sample split, the household weight was readjusted to reflect the new inflation rates in the calibration samples. The weight adjustment however, was not necessary in the validation sub-samples because the weight is not needed to predict the out-of-sample accuracy of the models. Obviously, the same level of accuracy cannot be guaranteed in such smaller samples. Table 1 describes the number of indicators and the sample size by model types.

[8] All variables with a bivariate correlation coefficient of more than 0.65 or a variance inflation factor of more than 10 were removed from the sets.

Table 1. Sample size by model types

Sub-samples	Rural model	Urban model	Total
Total sample size	9,840	1,440	11,280
- calibration (2/3)	6,560	960	7,540
- validation (1/3)	3,280	480	3,760
Number of indicators	148	112	-

Source: Own results based on Malawi IHS2 data.

2.2.2 Estimation methods

Two estimation methods were applied. They included the Weighted Least Square (WLS) and Weighted Logit (WL) regressions. As stated earlier, both regressions were weighted in order to account for how much each household influences the final parameter estimates. A weighted regression is also appropriate in the presence of heteroscedasticity[9]. Both regression methods are widely used in the literature. However, there is a debate on the merits of welfare regressions versus binary poverty models. The Weighted Least Square[10] uses the full information available by estimating the model over the entire welfare spectrum, whereas the Weighted Logit collapses the entire expenditure distribution into two values. In their poverty regressions, Braithwaite et *al.* (2000) justify the use of binary probit by the possibility of systematic measurement errors in the dependent variable. These authors also add that it is a judgment call whether the loss of information embodied in the binary regression outweighs the risk of bias due to measurement error. In this paper, we systematically compare the targeting performances of both methods to derive the best for targeting poor households and improving the efficiency of development policies.

[9] One of the critical assumptions of ordinary least square regression is homoscedasticity. When this assumption is violated, WLS compensates for violation of the homoscedasticity assumption by weighting cases differentially. Cases with greater weight contribute more to the fit of the regression. The result is that the estimated coefficients under the WLS have smaller standard errors.

[10] For example, Grosh and Baker (1995) argue that strictly speaking, ordinary least square is not appropriate for predicting poverty. Glewwe (1992) and Ravallion and Chao (1989) try to solve the problem of targeting using more complex poverty minimization algorithms. These methods are however difficult to implement and have limited applications compared to the methods used in this paper.

Both methods sought to identify the best set of ten indicators for predicting the household poverty status. Previous researches show that in general, the higher the number of indicators, the higher the achieved accuracy (Zeller and Alcaraz V., 2005; Zeller et *al.*, 2005). Higher accuracy is often achieved at a cost of practicality and entails higher costs of data collection. Therefore, we limited the number of indicators to the best ten in order to balance the cost of data collection, practicality, or operational use of the models. Furthermore, most analysts favor the use of ten regressors in an operational poverty targeting model.

A model with a high explanatory power is a prerequisite for good predictions of the dependent variable per capita daily expenditures (and thereby poverty status). Therefore, under the WLS, the best ten regressors were selected based on the Stepwise-MAXR routine of SAS (SAS Institute, 2003) that maximizes a model's explained variance (R-square). Under the WL, the best ten regressors were selected using the stepwise score routine of SAS. Similarly to the MAXR routine, SAS offers a stepwise score routine for best subset selection of variables with logistic regressions. The stepwise-score uses the branch and bound algorithm of Furnival and Wilson (1974) to find a specified number of models with the highest likelihood score (chi-square) statistic (SAS Institute, 2003). In other words, the stepwise-score seeks the best set of variables that maximizes the likelihood score (chi-square) statistic.

The WLS used the continuous dependent variable logarithm of daily per capita expenditures[11], whereas the WL had as dependent variable a dummy variable that is coded one if the household is poor (expenditures below the national poverty line) and zero otherwise. In other words, the WL model estimates the probability of a household being below the poverty line.

In the rural model, we controlled for agricultural development districts in order to capture agro-ecological and socioeconomic differences between regions. The inclusion of such variables also captures the effects of omitted variables as well as the effects of other

[11] The logarithm of expenditures was used instead of simple expenditures because the log function better approximates a normal distribution.

unobservable factors in the model. Likewise, in the urban model we controlled for the four major cities: Mzuzu, Zomba, Lilongwe, and Blantyre. Using the calibration samples, we estimated both models following Greene (2003) and Wooldridge (2006):

- *Weighted Least Square*

$$y_i = \beta_o + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i \qquad \textbf{(1)}$$

where y_i is the logarithm of daily per-capita expenditures, $x_{ik}, k = 1....K$ *and* $i = 1....n$ is the set of poverty predictors, including the control variables, β_o is the intercept term, $\beta_k, k = 1...K$ are the parameter estimates, ε_i is the random disturbance, n is the total number of observations in the sample. $\hat{y}_i$, the predicted value of y_i is estimated by:

$$\hat{y}_i = \hat{\beta}_o + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_k x_{ik} \qquad \textbf{(2)}$$

A weighted sum of residual squares is minimized to obtain the parameters as follows:

$$\min \sum_{i=1}^{n} \omega_i (y_i - \hat{y}_i)^2 \qquad \textbf{(3)}$$

$\omega_i, i = 1...n$ is the weight of observation i in the population.

- *Weighted Logit*

$$\rho_i (z_i = 1 | x_i) = \frac{1}{1 + e^{-\eta_i}} \qquad \textbf{(1)}$$

ρ_i is the probability of being poor, e is an exponential function, z_i is the poverty status variable, $z_i = \begin{cases} 1 \ (poor) \ if \ \rho_i \geq cut\text{-}off \\ 0 \ (non\text{-}poor), \ otherwise \end{cases}$ **(2)**

η_i is the linear predictor, $\eta_i = \alpha_o + \alpha_1 x_{i1} + \alpha_2 x_{i2} + \ldots + \alpha_k x_{ik} + \varepsilon_i$ **(3)**

$x_{ik}, k = 1....K \text{ and } i = 1....n$ is the set of poverty predictors, including the control variables, α_o is the intercept term, $\alpha_{1k}, k = 1...K$ are the parameter estimates, ε_i is the random disturbance. The estimated logit or natural log ($\ln$) of the odds is given by:

$$\ln\left(\frac{\hat{\rho}_i(z_i = 1|x_i)}{1-\hat{\rho}_i(z_i = 1|x_i)}\right) = \hat{\alpha}_o + \hat{\alpha}_1 x_{i1} + \hat{\alpha}_2 x_{i2} + ... + \hat{\alpha}_k x_{ik} \tag{4}$$

A weighted Maximum Likelihood Estimator (MLE) is maximized to obtain the parameters as follows:

$$MLE = \max \sum_{i=1}^{n} \omega_i \left[\left\{ z_i \ln\left(\frac{1}{1+e^{-\hat{\eta}_i}}\right) \right\} + \left\{ (1-z_i)\ln\left(1-\frac{1}{1+e^{-\hat{\eta}_i}}\right) \right\} \right] \tag{5}$$

$\omega_i, i = 1...n$ is the weight of observation i in the population.

The distinction between exogenous and endogenous variables in the holistic causal chain of poverty is difficult to make in practice: feedback loops and endogeneity issues can be conceptualized virtually everywhere in this chain (Grootaert and Braithwaite, 1998). But since the purpose of a poverty assessment is to measure poverty (i.e., to identify and use highly significant but easily measurable correlates of poverty) and not to analyze causal relationships, it is analytically permissible to measure primary causes (lack of entitlements, rights, and endowments) together with intermediate and final outcome variables in the consumption, production, and investment spheres of individuals and their households as possible indicators of poverty. Therefore, the above models do not seek to identify the determinants of poverty, but select variables that can best predict the current poverty status of a household. A causal relationship should not be inferred from the results.

2.2.3 Predicting the household poverty status

Having estimated the model, the question arises as to what cut-off to use to predict the household poverty status. We therefore explored three classifications based on three different cut-offs: *national, percentile-corrected*, and *maximum-BPAC* cut-offs.

In the first classification, the predicted per capita expenditures from the WLS were compared to the *national poverty line* to derive the *predicted household poverty status.* Households with per capita expenditures less than MK44.29 daily were classified as *poor* and those with higher daily per capita expenditures were deemed *non-poor*. The national poverty line matches the actual poverty rate in the total population. Similarly, the probability of being poor estimated with the WL regression was compared to the cut-off point (predicted probability) that matches the actual poverty rate in the population. Households with higher probability than this cut-off point were predicted as *poor*, otherwise they were deemed *non-poor*.

However, the above classification ignores the unknown error in the estimation of household expenditures. As a result, it would give biased estimates of poverty rates (Hentschel et *al*., 2000) and thereby accuracy performances. Therefore, a second classification based on the *percentile-corrected poverty line* (PC) was used[12]. Figure 1 illustrates the national and percentile-corrected poverty lines from the WLS method. As shown in the graph, the PC poverty line is the line that matches the actual poverty rate in the distribution of predicted expenditures after the rural model's estimation. Both poverty lines on the graph differ, but the difference between them is minor since the vertical lines are very close to each other.

[12] See Johannsen (2009) for further details on the percentile-corrected approach.

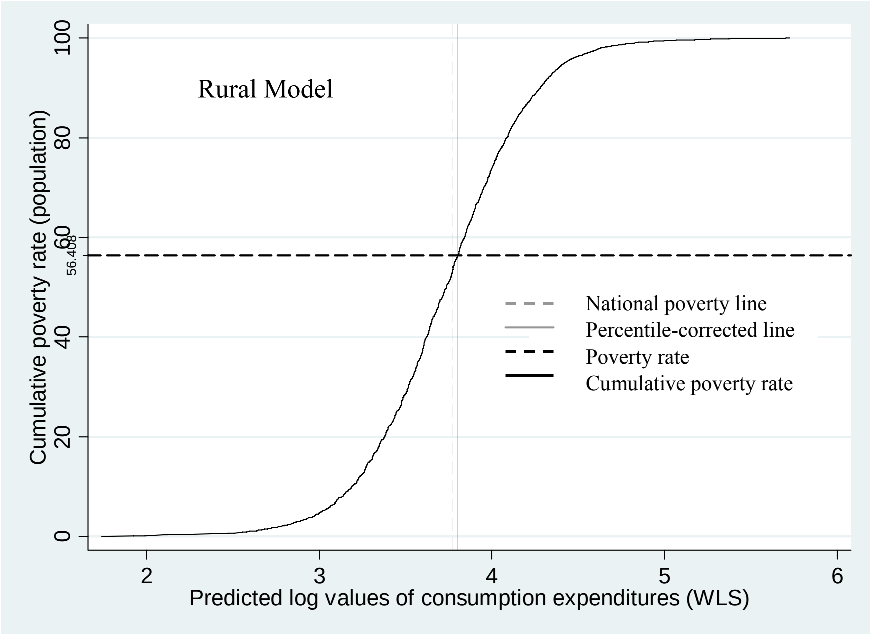


Figure 1. Cumulative distribution of poverty rate.
Source: Own results based on Malawi IHS2 data.

The third classification approach used to predict the household poverty status applied the cut-off that maximizes the *Balanced Poverty Accuracy Criterion* (BPAC)[13] which is an estimation method overall performance measure. Table 2 summarizes the decision rule for predicting the household poverty status.

Table 2. Decision rule for predicting the household poverty status

Method Classification type	**Weighted Least Square**	**Weighted Logit**
Cut-off 1	Poverty line	Probability that matches the poverty line
Cut-off 2	Percentile-corrected line (PC)	Probability that matches the PC line
Cut-off 3	Poverty line that maximizes the BPAC*	Probability that maximizes the BPAC

Source: Own presentation. *See section 2.3 for details on BPAC.

The three poverty classifications in Table 2 were then crossed with the *actual household poverty status*. The latter was determined by comparing the actual daily per capita expenditures to the national poverty line as in the first classification above. The two-by-two cross-table of the actual and predicted household poverty statuses was subsequently used to describe the outcomes of the predictions as exemplified in Table 3.

[13] See section 2.3 for further details on BPAC.

Table 3. Net benefit matrix of poverty classification (hypothetical figures)

Actual poverty status	Predicted poverty status		
	Non-poor	Poor	Total
Non-poor	20	15	35
Poor	10	5	15
Total	30	20	50

Source: Own presentation.

Table 3 suggests that 5 out of 15 actually poor households were correctly predicted as poor, whereas the remaining 10 households were wrongly predicted as non-poor. Likewise, 20 of 35 actually non-poor households were correctly predicted as non-poor, while the remaining 15 households were wrongly predicted as poor. The above example suggests that the net benefit matrix yields correct as well as incorrect predictions of the household poverty status. Based on the results, different performance measures can then be calculated as described in section 2.3.

2.3 Accuracy measures and robustness tests

2.3.1. Accuracy measures

Different measures have been proposed in the literature on poverty targeting to assess the accuracy of a poverty assessment model. This paper focuses on selected ratios which are especially relevant for targeting the poor (Table 4).

Table 4. Selected accuracy ratios

Targeting ratios	Definitions
Poverty Accuracy	Number of households correctly predicted as poor, expressed as a percentage of the total number of poor
Undercoverage	Number of poor households predicted as non-poor, expressed as a percentage of the total number of poor
Leakage	Number of non-poor households predicted as poor, expressed as a percentage of the total number of poor
Poverty Incidence Error (PIE)	Difference between predicted and actual poverty incidence, measured in percentage points
Balanced Poverty Accuracy Criterion (BPAC)	Poverty accuracy minus the absolute difference between undercoverage and leakage, measured in percentage points

Source: Adapted from IRIS (2005).

The poverty accuracy is self-explanatory. Undercoverage and leakage are extensively used in the literature to assess the targeting efficiency of development policies (Valdivia, 2005; Ahmed et *al.*, 2004; Weiss, 2004). The Poverty Incidence Error (PIE) indicates the precision of the model in correctly predicting the poverty incidence. Ideally, the value of PIE should be zero, implying that the predicted poverty rate equals the observed poverty rate. Positive values of PIE indicate an overestimation of the poverty incidence, whereas negative values imply the opposite. The PIE is particularly useful in measuring the poverty outreach of an institution that provides microfinance or business development services.

The Balanced Poverty Accuracy Criterion (BPAC) considers the first three accuracy measures above because of their relevance for poverty targeting. These three measures exhibit trade-offs. For example, minimizing leakage leads to higher undercoverage and lower poverty accuracy. Higher positive values for BPAC indicate higher poverty accuracy, adjusted by the absolute difference between undercoverage and leakage. In this paper, the BPAC is used as the overall criterion to judge a method’s accuracy performance. In the formulation of the BPAC, it is assumed that leakage and undercoverage are equally valued. For example, Ravallion (2007) found it more credible to value both measures in a characterization of a policy problem. However, a policy maker may give higher or lower weight to undercoverage compared to leakage. This is in principle possible by altering the weight for leakage in the BPAC formula.

2.3.2 Assessing the predictive power and robustness of the models

Out-of-sample validation tests were performed to ascertain the predictive power and the robustness of the models. The main purpose of the validation is to observe how well the models perform in an independent sample derived from the same population. A model with high predictive power in a validation sample is relevant for reaching most of the poor. Therefore, the models developed were validated by applying the set of selected indicators, their weights, and cut-offs to the validation sub-samples in order to predict the household poverty status.

Furthermore, the model robustness was assessed by estimating the prediction intervals of the targeting ratios out-of-sample using bootstrapped simulation methods. Approximate confidence interval based on bootstrap computations were introduced by Efron in 1979 (Efron, 1987; Horowitz, 2000). Bootstrap is the statistical procedure which models sampling from a population by the process of resampling from the sample (Hall, 1994). Using the bootstrap approach, repeated random samples of the same size as the validation sub-samples were drawn with replacement. The set of identified indicators and their derived weights were applied to each resample to predict the household poverty status and estimate the accuracy ratios. These bootstrap estimates were then used to build up an empirical distribution for each ratio. Unlike standard confidence interval estimation, bootstrap does not make any distributional assumption about the population and hence does not require the assumption of normality.

A thousand (1,000) new samples were used for the estimations. Campbell and Torgerson (1999) state that the number of bootstrap samples required depends on the application, but typically it should be at least 1,000 when the distribution is to be used to construct confidence intervals. Figure 2 illustrates the distribution of the poverty accuracy for 1,000 samples for the best ten indicator set. This graph is superimposed with a normal curve.

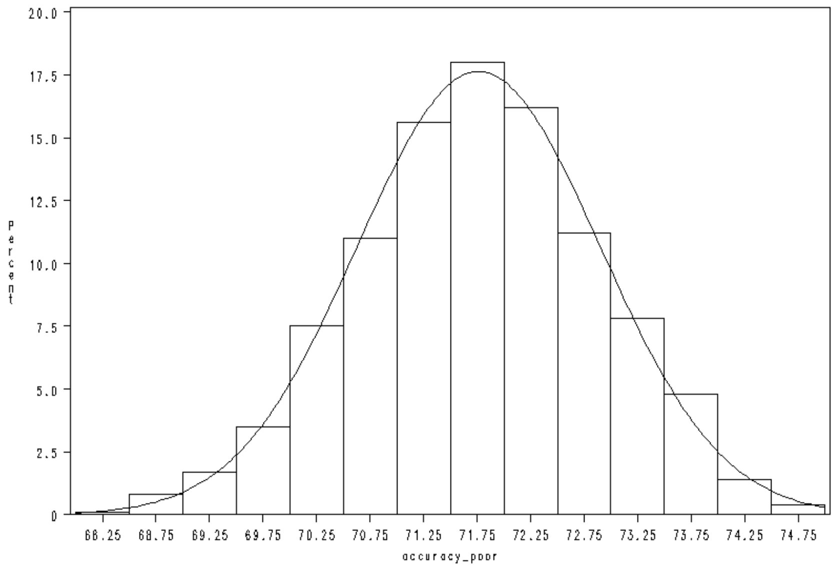


Figure 2: Bootstrapped distribution of the poverty accuracy (WLS).
Source: Own results based on Malawi IHS2 data.

After generating the bootstrap distribution, the 2.5th and 97.5th percentiles were used as limits for the interval at a 95% confidence level. This amounts to cutting the tails of the above distribution on both sides.

3. Results and Discussions

This section discusses the out-of-sample results of the models[14]. First, we briefly describe the poverty lines applied. Then, the targeting performances of the models are presented by regression methods and poverty classifications. The classification that yields the highest performances is selected and flagged with the prediction intervals. We then compare the aggregate accuracy of both estimation methods out-of-sample. Finally, we analyze the sensitivity of the models to the poverty line and the distribution of targeting errors.

3.1 Modelling the household poverty status: Empirical results

Table 5 gives an overview of the poverty lines and rates in Malawi. The full regression results, including the indicator lists are presented in Annex 1 thru 4. All of the coefficient

[14] For brevity reasons, only out-of-sample results are presented throughout the paper. The results from the model calibrations are available upon request.

estimates on the best indicator sets are statistically significant and their signs are consistent with expectations and economic theory.

Table 5. Malawi's poverty rates by regions and poverty lines (as of 2005)[15]

Type of poverty line	Poverty lines (MK*)	Poverty rate (in percent of people)			Poverty rate (in percent of households)		
		national	rural	urban	national	rural	urban
Extreme	29.81	26.21	28.66	8.72	19.94	22.08	5.95
National	44.29	52.40	56.19	25.23	43.58	47.13	19.67
International	59.18 (US$1.25 PPP)	69.52	73.59	40.26	61.04	65.20	33.08

Source: Own results based on Malawi IHS2 data, Chen and Ravallion (2008), and the World Bank (2008). MK denotes Malawi Kwacha, national currency. PPP stands for Purchasing Power Parity.

As shown in Table 5, the poverty rate in Malawi is estimated at 52.4% under the national poverty line of MK44.29. This rate suggests that more than half the population is unable to meet their basic needs. However, the poverty rate varies considerably between urban and rural areas. Following Chen and Ravallion (2008), the international poverty line of US$1.25 was used. Converted to Malawi Kwacha (MK) using the 2005 Purchasing Power Parity (World Bank, 2008), the international poverty line is equivalent to MK59.18 per day. Under this line, the national poverty headcount is estimated at 69.52%. This line hides sizeable differences between urban and rural areas. The extreme poverty line is defined as the line under which the poorest 50% of the population below the national poverty line are living. This line was set at MK29.31. Under the extreme poverty line, 26% of Malawians are very poor. These poverty rates are lower when expressed in percent of households. Table 6 presents the results of the rural model by classification types.

[15] These rates differ slightly from the official statistics because of errors in the weights of the IHS2 report.

Table 6. Rural model's predictive accuracy by classification types

Targeting ratios Method	Cut-off	Log cut-off value (MK)	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
WLS	***National***	3.79	64.07	35.94	20.45	-7.32	48.58
	Percentile	3.80	65.43	34.58	21.74	-6.07	52.58
	MaxBPAC	3.85	72.00	28.00	26.32	-0.79	70.32
WL	***National***	0.59	58.77	41.23	16.58	-11.65	34.13
	Percentile	0.66	48.85	51.16	11.42	-18.78	9.10
	MaxBPAC	0.48	71.61	28.39	27.10	-0.61	70.32

Source: Own results based on Malawi IHS2 data.

Table 6 suggests that under the WLS method, the cut-off that maximizes the BPAC in-sample (*MaxBPAC*) yields the highest out-of-sample performances, followed by the percentile-corrected poverty line, and then the national poverty line. The highest BPAC is however, associated with the highest leakage. The same trend applies to the WL method; except that the percentile-corrected poverty line yields the lowest performances in that case. The results show that the classification by the *MaxBpac* cut-off consistently yields the highest BPAC out-of-sample.

These results also illustrate the trade-off between undercoverage and leakage ratios as increasing the cut-off[16] reduces the undercoverage (improves poverty accuracy), but results in higher leakage to the non-poor. The performances of the urban model (see annex 5) follow the same pattern as the rural model. Therefore, the cut-off that maximizes the BPAC in the calibration sample was selected as the optimal cut-off for out-of-sample validations. Table 7 describes the results of the rural and urban models at these optimal cut-offs, including their prediction intervals.

[16] This trade-off also applies to the WL method, but when reducing the cut-off because the method estimates the probability of being poor.

Table 7. Model predictive accuracy at optimal cut-offs

Targeting ratios Model	Method	Cut-off values (MK)	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
Rural	***WLS***	3.85	**72.00** (69.7; 74.2)	**28.00** (25.8; 30.3)	**26.32** (23.4; 29.1)	**-0.79** (-2.4; 1.0)	**70.32** (64.9; 73.5)
	WL	0.48	**71.61** (69.6; 74.0)	**28.39** (26.0; 30.4)	**27.10** (24.2; 30.0)	**-0.61** (-2.3; 1.1)	**70.32** (65.2; 73.2)
Urban	***WLS***	3.92	**62.16** (53.3; 71.0)	**37.84** (29.0; 46.7)	**38.74** (26.3; 52.8)	**0.21** (-3.5; 3.8)	**61.26** (40.9; 66.5)
	WL	0.39	**61.26** (51.7; 70.5)	**38.74** (29.5; 48.3)	**39.64** (27.3; 53.5)	**0.21** (-3.2; 4.0)	**60.36** (40.9; 66.0)

Source: Own computations based on Malawi IHS2 data. Bootstrapped prediction intervals in brackets. Cut-off values are expressed in Ln MK under the WLS and probability for the WL.

Table 7 shows that the WLS method yields a poverty accuracy of 72% and a BPAC of 70.32% points for the rural model. This result indicates that the model would cover about 72% of the poor - that is about seven out of every ten poor households - if applied to target Malawi's poor. The undercoverage is estimated at 28%, while the leakage is set at 26.32% for the same model and estimation method. The PIE nears 0% points, which implies that the method perfectly predicts the poverty rate out-of-sample. Likewise, the WL method yields a poverty accuracy of about 72% and a BPAC of 70.32% points for the rural model. In addition, the estimated PIE is close to 0% points, whereas undercoverage and leakage are estimated at 28.39% and 27.10%, respectively. These results show that the WLS and the WL yield the same BPAC and PIE, but the former slightly outperforms the latter in terms of poverty accuracy and leakage. Using the BPAC to assess an estimation method's overall accuracy, the results of the rural model show that both methods perform equally. Even when considering single accuracy measures, such as poverty accuracy or leakage, both methods do not differ much in terms of targeting performances.

With regard to the urban model, Table 7 indicates that the WLS and WL methods yield the same PIE of 0.21% points which indicate that they both predict the poverty rate remarkably well. However, the former yields a slightly higher BPAC (61.26% points) and poverty accuracy (62.16%) compared to the latter. Besides, its leakage is lower (38.74%).

Though the WLS method slightly outperforms the WL method, the results of the urban model show that the differences in performances between both methods are minor. Nonetheless, the leakage and undercoverage are deceptively high in the urban model.

The relatively low performance of the urban model as compared to the rural model is partly driven by the low level of actual poverty rate in urban areas: 25% versus 56%. Therefore, the lower the poverty rate, the weaker the model performance. This result may also be due to the greater variability in the welfare indicator for urban households and between different urban centers in Malawi. The variance estimates of the household consumption expenditures point to this argument. Nevertheless, even though undercoverage and leakage are high in urban areas, these errors amount to relatively small numbers of households; less than 15% of Malawians live in urban areas.

As concerns the prediction intervals, Table 7 shows that the interval lengths are very short under the rural model with a maximum width of 8% points, indicating a very robust model. Conversely, the results of the urban model suggest a less robust tool with higher interval lengths. These results are explained by the lower size of the sample used to validate the urban model as shown in Table 1.

As a whole, the above findings suggest that both estimation methods perform equally, with the WLS slightly outperforming the WL[17]. Likewise, the rural model performs better than the urban model which is less robust. Section 2.3 compares the estimation method aggregate performances.

3.2 Estimation method aggregate performances

To compare the aggregate predictive power of the WLS and WL regressions, the Receiver Operating Characteristic (ROC) curves were plotted based on the predictions of the

[17] To allow for a stricter comparison of both estimation methods, we used in separate simulations the same indicator set to fit both regressions. The results however, do not differ from the performances presented.

validation samples. Unlike the results in section 3.1 which were based on a single cut-off – the cut-off that maximizes the BPAC in-sample –, the ROC curve shows the trade-off between the coverage of the poor or poverty accuracy and the inclusion of non-poor or inclusion error[18] at different cut-offs across the predicted welfare (WLS) or probability (WL) spectrum. Earlier applications of ROC curves for poverty assessment include Wodon (1997), Baulch (2002), and Schreiner (2006) who applied the curve in combination with probit or logit regression in a calibration sample only. However, apart from Johannsen (2009), no research has to our knowledge applied the ROC curve out-of-sample to assess the accuracy performances of different estimation methods.

Figure 3 displays the ROC curves of the rural model. In addition, Figure 4 illustrates the BPAC distributions across the cut-off spectrum.

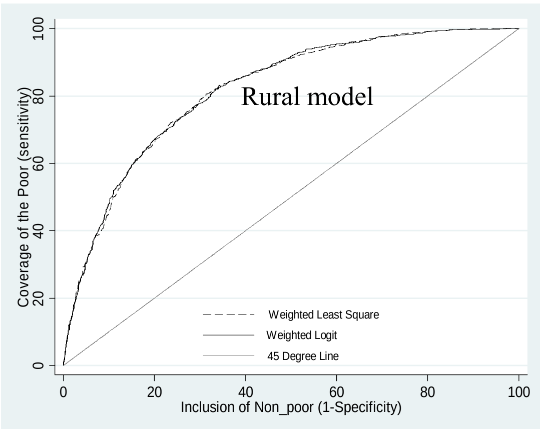


Figure 3: ROC curves of the rural model.
Source: Own results based on Malawi IHS2 data.

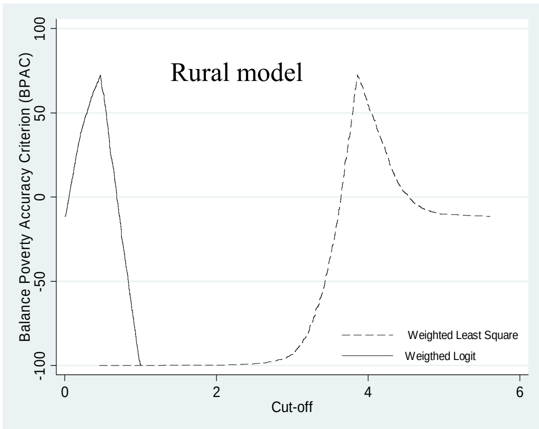


Figure 4: BPAC curves of the rural model.
Source: Own results based on Malawi IHS2 data.

Figure 3 shows that the higher the coverage of the poor, the higher the inclusion of non-poor. For example, 80% coverage of the poor would lead to an inclusion of about 30% of non-poor households. Increasing the coverage of the poor to 90% would lead to more than 40% of non-poor households being wrongly targeted. The curves follow a similar pattern with

[18] The coverage of the poor or poverty accuracy is also known as sensitivity, whereas the inclusion of non-poor or inclusion error is also termed as 1-specificity. It is defined as the error of predicting non-poor as poor, expressed in percent of non-poor. It differs from the leakage (Table 2) which is expressed in percent of poor.
See Wodon (1997) and Baulch (2002) for further details on ROC curves.

minor exceptions. While both curves are monotonically increasing, their shape depends on the performances underlying each model used to predict the poverty status of the households. The curves overlay in the lower (below 40% sensitivity level), middle (between 50% and 65% and between 85% and 90% sensitivity level), and extreme upper (above 95% sensitivity level) sections of the graph. This pattern illustrates that both curves achieve the same coverage of the poor in these sections of the graph. Between 40% and 50% sensitivity level, the WL yields slightly higher accuracy, whereas the WLS performs better the latter between 65% and 70% sensitivity level. These results suggest that none of the estimation methods consistently yields the highest coverage of the poor across the ROC curves. In the relevant band of sensitivity (from 70% to 90%) however, both methods perform equally.

Furthermore, by visual inspection the areas under the curves are not much different. To confirm this statement, we tested the difference between the distributions of poverty accuracy for both curves. The results of the tests show that there is no statistically significant difference between both distributions. Therefore, both estimation methods yield approximately the same level of aggregate predictive accuracy. This result is consistent with the findings in Table 7 which suggest that both methods do not differ much in terms of achieved targeting performances. More to this point, the accompanying BPAC curves (Figure 4) show that the maxima obtained out-of-sample (about 73% points) are not much different from the performances presented in Table 7. The reason behind is that the cut-offs applied to the validation sample are closer to the out-of-sample optima. This indicates that the cut-offs that maximize the BPAC in the calibration sample converge towards the out-of-sample optima[19]. The same trend applies to the urban model (Figures 5 and 6).

[19] A similar trend emerges when the models were calibrated to the international and extreme poverty lines.

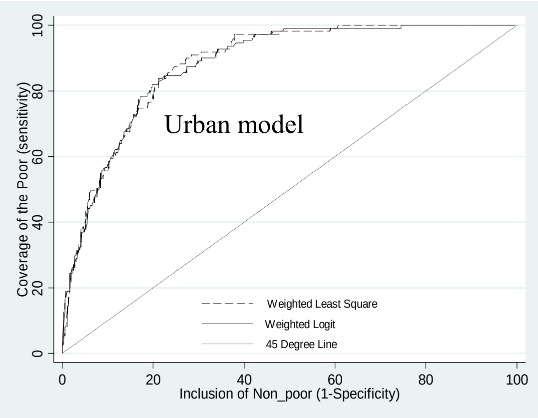


Figure 5: ROC curves of the urban model.
Source: Own results based on Malawi IHS2 data.

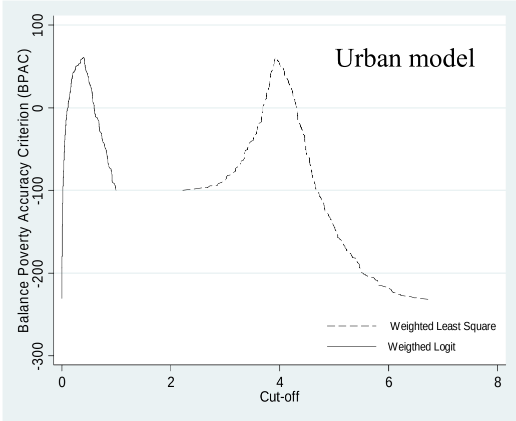


Figure 6: BPAC curves of the urban model.
Source: Own results based on Malawi IHS2 data.

Figure 5 indicates that in the relevant band of sensitivity (from 70% to 90%), the WL outperforms the WLS within the lower section of the band, whereas the WLS outperforms the WL in the upper section of the band. Likewise, the difference between the distributions of both curves is found to be statistically not significant. Therefore, both methods do not differ in terms of aggregate predictive accuracy. This result is consistent with the findings in Table 7.

As stated earlier, the cut-off that maximizes the BPAC in the calibration sample is used to judge a method's overall targeting performance out-of-sample. However, a policy maker may set a different cut-off using the ROC curve to decide on the number of poor a program or project should reach and ponder on the number of non-poor that would be incorrectly targeted. The best indicators selected are objective and fairly easy to verify (see regression results in the annex). Information on these indicators can be quickly collected at low cost by a survey agent to determine the household poverty status.

3.3 How do the model results change with the poverty line?

In this section, we examine the sensitivity of the models to the choice of the poverty line. These simulations involved the calibration of the models to the international and extreme poverty lines described in Table 5. Under the WLS method, the list of the best indicators selected is the same across poverty lines. However, since the dependent variable in the WL method - the household poverty status - is affected by the poverty line chosen, the logit regression, including the selection of indicators was re-estimated for both lines and models. Table 8 shows the results of the simulations.

Table 8. Model sensitivity to poverty line

Method	Targeting ratios / Poverty line*	Cut-off values (MK)	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
			Rural Model				
WLS	*International*	4.03	**82.33** (80.9; 83.9)	**17.67** (16.1; 19.1)	**16.60** (14.7; 18.4)	**-0.70** (-2.3; 1.0)	**81.27** (77.7; 83.3)
	Extreme	3.56	**49.93** (46.4; 53.4)	**50.07** (46.6; 53.6)	**39.21** (34.2; 44.4)	**-2.44** (-3.9; -1.0)	**39.08** (30.9; 48.1)
WL	*International*	0.56	**82.61** (81.1; 84.2)	**17.39** (15.8; 18.9)	**16.18** (14.4; 18.1)	**-0.79** (-2.2; 0.9)	**81.40** (77.9; 83.6)
	Extreme	0.36	**53.05** (49.6; 56.7)	**46.95** (43.3; 50.4)	**38.54** (33.5; 44.1)	**-1.89** (-3.4; -0.4)	**44.64** (35.9; 53.7)
			Urban Model				
WLS	*International*	4.18	**74.57** (68.3; 81.2)	**25.43** (18.8; 37.1)	**24.86** (17.4; 34.2)	**-0.21** (-3.8; 3.7)	**73.99** (59.5; 77.6)
	Extreme	3.52	**50** (31.8; 67.7)	**50** (32.3; 68.2)	**73.53** (43.7; 123.0)	**1.67** (-0.8; 4.2)	**26.47** (-23.4; 50.5)
WL	*International*	0.43	**73.99** (67.7; 79.9)	**26.01** (20.1; 32.3)	**26.59** (18.6; 36.2)	**0.21** (-3.6; 4.0)	**73.41** (59.5; 76.6)
	Extreme	0.30	**47.06** (31.0; 64.7)	**52.94** (35.3; 69.0)	**61.77** (32.1; 104.4)	**0.63** (-1.9; 3.1)	**38.23** (-5.61; 51.7)

Source: Own results based on Malawi IHS2 data. WLS= Weighted Least Square, WL= Weighted Logit. Prediction intervals in brackets. Cut-off values are expressed in Ln MK under the WLS and probability for the WL. *See Table 5 for description of poverty lines.

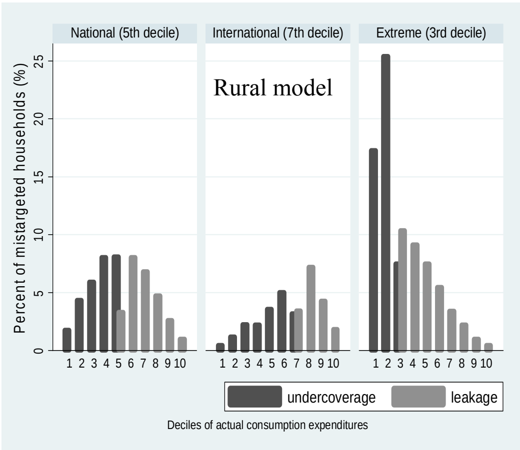
Table 8 shows that raising the poverty line to US$1.25 (MK59.18 PPP) increases the BPAC and the coverage of the poor by about 10% to 14% points and reduces the leakage by the same margin depending on the model and estimation method applied. These results suggest a sizable improvement of model targeting performances with about 82% and 74% of the poor correctly targeted by the rural and urban models, respectively. Nearly, all poor households are identified and covered in these scenarios.

On the other hand, reducing the poverty line to MK29.31 disappointingly reduces the targeting performances of the rural model by 10% to 30% points depending on the ratio and estimation method. Under the urban model, the reduction in targeting performances ranges from 12% to 35% points. Likewise, both models estimate the observed poverty rate remarkably well when calibrated to the international poverty line as compared to the extreme poverty line; in which case the deviation from the observed poverty rate is much higher as shown by the PIE.

Furthermore, the results show that given the model, both estimation methods do not differ much in terms of performances when calibrated to the international poverty line. On the contrary, the difference between both methods is more perceptible when calibrated to the extreme poverty line. The comparison of the ROC curves point towards the same conclusion (see annex 6 thru 9). These results confirm the findings in Table 7 and the conclusions regarding the ROC curves in Figures 3 and 5. The following section analyzes the distribution of model targeting errors across poverty deciles.

3.4 Targeting error distribution

As we have seen in the previous sections, irrespective of the poverty line and estimation method applied, the models yield some targeting errors, though these errors decrease with increasing poverty line. This is due to inherent model estimation errors. While it is unsatisfactory to miss the poor or wrongly target the non-poor, the error would be less severe if indeed those who are excluded are the least poor or those who are incorrectly targeted are the least rich households (Grosh and Baker, 1995). To confirm this, we looked at the out-of-sample distribution of model undercoverage and leakage by deciles of actual consumption expenditures for the three poverty lines applied (Figures 7 and 8).



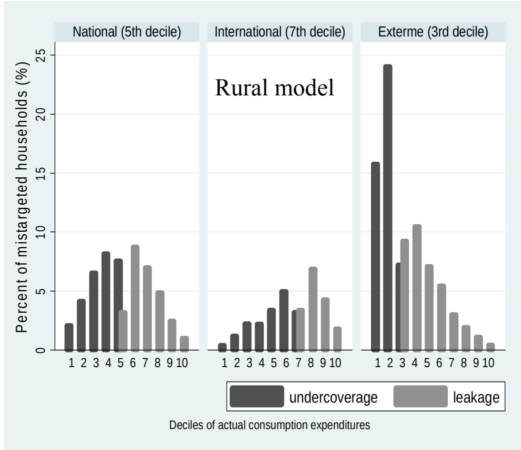


Figure 7: Targeting errors by poverty lines (WLS). Source: Own results based on Malawi IHS2 data.

Figure 8: Targeting errors by poverty lines (WL). Source: Own results based on Malawi IHS2 data.

Figure 7 shows that when the rural model is calibrated to the national poverty line, poor households whom the model fails to cover are heavily concentrated among those just under the line in the 5th decile rather than at the very bottom of the welfare distribution, while those who are incorrectly targeted are heavily concentrated among those just above the national poverty line rather than at the top of the distribution. The same trend applies to the international and extreme poverty lines, and the WL estimation method (Figure 8).

These results suggest that the models perform quite well in terms of poor households who are incorrectly excluded and non-poor who are wrongly targeted; covering most of the poorest deciles and excluding most of the richest ones. The same trend applies to the urban model ((see annexes 10 and 11). These results have obvious desirable welfare implications. They are also consistent with Coady and Parker (2009) who found that administrative selection based on proxy-means testing is particularly effective at reducing overall program coverage while maintaining high coverage of the lowest welfare households.

4. Concluding Remarks

This paper proposes empirical models for improving the poverty outreach of agricultural and development policies in Malawi. Furthermore, the research analyzes the out-of-sample performances of two estimation methods in targeting the poor. The developed models were calibrated to three different poverty lines as a set of policies might explicitly target different poverty groups in the population.

Findings suggest that both estimation methods achieve the same level of targeting performances out-of-sample. This is confirmed by the ROC curves which show that there is no sizable difference in aggregate predictive accuracy between both methods. Likewise, calibrating the models to a higher poverty line improves their targeting performances, while calibrating the models to a lower line does the opposite. With regard to targeting errors, the models perform well in terms of those who are mistargeted; covering most of the poorest deciles and excluding most of the richest ones.

The set of selected indicators are easily observable and fairly easy to verify. This implies a simple and low-cost system to identify the poor. The models developed can be used to improve the existing targeting mechanisms of agricultural input programs in the country. Furthermore, they can be applied to target a wide range of development policies at the poor and estimate poverty rates over time. Similarly, they can be used to assess the poverty impacts of such policies. However, the observed patterns could be refined with additional validations across time as suitable data become available. Likewise, the estimations of the potential impacts of the models on poverty, its benefits, and costs are left out for further research.

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Annexes

Annex 1. Weighted Least Square regression results (rural model)

Adj. R^2 = 0.4597 Model significance F= 329.25*** Number of observations= 6560

	Indicator set	Parameter Estimates	Standard Errors	T-values
	Intercept	4.337***	0.037	115.86
Control variables	Agricultural development district is Mzuzu	0.078**	0.038	2.07
	Agricultural development district is Kasungu	0.257***	0.037	6.96
	Agricultural development district is Salima	0.164***	0.039	4.21
	Agricultural development district is Lilongwe	0.220***	0.035	6.38
	Agricultural development district is Machinga	-0.079**	0.034	-2.31
	Agricultural development district is Blantyre	-0.036	0.034	-1.04
	Agricultural development district is Ngabu	0.009	0.040	0.24
Best 10 indicators	1. Household size	-0.169***	0.003	-60.94
	2. Number of members who can read in English	0.082***	0.006	14.36
	3. Household grew tobacco in the past five cropping seasons	0.119***	0.016	7.63
	4. Floor of main dwelling is predominantly made of smooth cement	0.192***	0.019	10.19
	5. Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0.047***	0.005	9.41
	6. Cooking fuel is collected firewood	-0.152***	0.017	-9.06
	7. Bed ownership	0.161***	0.016	10.35
	8. Tape, CD player, or HiFi ownership	0.179***	0.018	9.67
	9. Electric, gas stove, or hot plate ownership	0.610***	0.067	9.16
	10. Bicycle ownership	0.154***	0.013	12.31

Source: Own results based on Malawi IHS2 data. *** *denotes significant at the 99% level.*
** *denotes significant at the 95% level.*

Annex 2. Weighted Logit regression results (rural model)

	Indicator set	Parameter Estimates	Standard Errors	Wald Chi-Square
	Likelihood ratio = 877042.545*** Score= 721528.131***		Wald=520598.859*** Number of observations= 6560	
Control variables	Intercept	-1.496***	0.010	22891.540
	Agricultural development district is Mzuzu	-0.478***	0.011	1972.800
	Agricultural development district is Kasungu	-1.258***	0.011	13756.947
	Agricultural development district is Salima	-0.326***	0.011	887.511
	Agricultural development district is Lilongwe	-0.973***	0.010	9748.009
	Agricultural development district is Machinga	0.293***	0.010	914.526
	Agricultural development district is Blantyre	0.031***	0.010	9.969
	Agricultural development district is Ngabu	-0.068***	0.011	35.864
Best 10 indicators	1. Household size	0.703***	0.001	421164.019
	2. Number of male adults in the household	-0.276***	0.003	11877.869
	3. Number of members who can read in English	-0.302***	0.002	29751.164
	4. Household has grew tobacco in the past five cropping seasons	-0.482***	0.004	11686.453
	5. Floor of main dwelling is predominantly made of smooth cement	-0.971***	0.006	29707.046
	6. Any household members sleep under a bed net?	-0.451***	0.004	14831.047
	7. Bed ownership	-0.558***	0.004	15565.326
	8. Tape, CD player, or HiFi ownership	-0.708***	0.006	15968.654
	9. Bicycle ownership	-0.481***	0.004	17194.069
	10. Paraffin lantern ownership	-0.485***	0.004	15156.778

Source: Own results based on Malawi IHS2 data. **** denotes significant at the 99% level.*
*** denotes significant at the 95% level.*

Annex 3. Weighted Least Square regression results (urban model)

Model significance F= 176.05***

Adj. R^2 = 0.7035 Number of observations= 960

	Indicator set	Parameter Estimates	Standard Errors	T-values
Control variables	Intercept	4.903***	0.074	66.14
	Lilongwe city	0.061	0.063	0.97
	Zomba city	-0.351***	0.084	-4.19
	Blantyre city	-0.200***	0.063	-3.15
Best 10 indicators	1. Household size	-0.240***	0.009	-28.20
	2. Number of members who can read in English	0.073***	0.013	5.84
	3. Maximum class level ever attended in the household is superior/post secondary	0.413***	0.070	5.91
	4. Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0.083***	0.016	5.07
	5. Cooking fuel is collected firewood	-0.419***	0.052	8.08
	6. Household owns a landline telephone in working condition?	0.351***	0.079	4.45
	7. Household has electricity working in the dwelling	0.316***	0.043	7.29
	8. Bed ownership	0.263***	0.038	6.87
	9. Television & VCR ownership	0.333***	0.061	5.51
	10. Electric, gas stove, or hot plate ownership	0.263***	0.060	4.38

Source: Own results based on Malawi IHS2 data. **** denotes significant at the 99% level.*
*** denotes significant at the 95% level.*

Annex 4. Weighted Logit regression results (urban model)

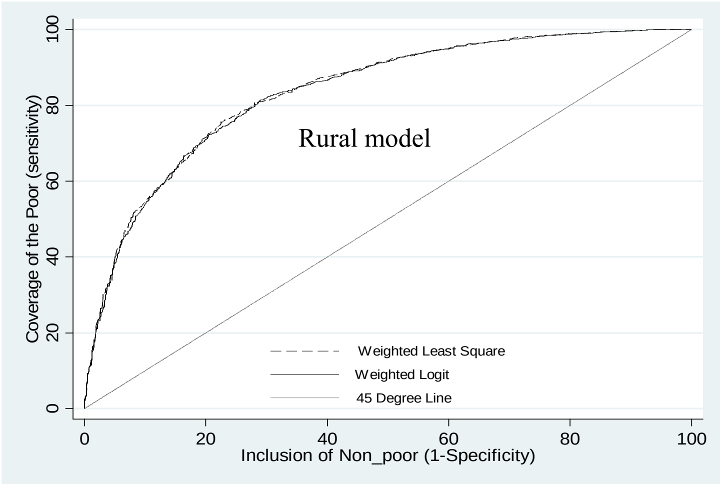
	Indicator set	Parameter Estimates	Standard Errors	Wald Chi-Square
Likelihood ratio= 140465.169*** Score= 123575.755***		Wald= 63111.546*** Number of observations= 960		
Control variables	Intercept	-3.913***	0.036	12181.583
	Lilongwe city	0.035	0.023	2.390
	Zomba city	1.012***	0.030	1168.705
	Blantyre city	0.987***	0.024	1704.266
Best 10 indicators	1. Household size	0.721***	0.004	40401.758
	2. Number of members who can read in English	-0.124***	0.005	636.188
	3. Household can read in Chichewa language	-0.672***	0.015	2114.769
	4. Highest class level ever attended by females in the household is secondary/post primary	-1.466***	0.020	5294.979
	5. Dwelling construction material is traditional	0.862***	0.015	3499.259
	6. Cooking fuel is collected firewood	0.926***	0.017	2905.106
	7. Household has electricity working	-1.751***	0.025	5094.946
	8. Household head sleeps on Mat (grass) on floor	1.021***	0.0133	5903.420
	9. Television & VCR ownership	-2.108***	0.0473	1984.649
	10. Is there a place to purchase common medicines such as panadol in this community?	-0.831***	0.0202	1697.948

Source: Own results based on Malawi IHS2 data. **** denotes significant at the 99% level.*
*** denotes significant at the 95% level.*

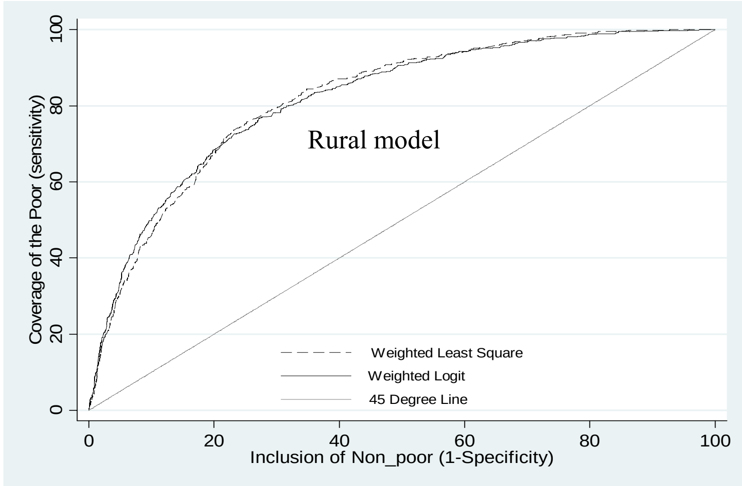
Annex 5. Urban model's predictive accuracy by type of classifications

Targeting ratios		Cut-off probability	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
WLS	***National***	3.79	49.55	50.45	23.42	-6.25	22.52
	Percentile	3.85	55.86	44.14	31.53	-2.92	43.24
	Max BPAC	3.92	62.16	37.84	38.74	0.21	61.26
WL	***National***	0.32	67.57	32.43	46.85	3.33	53.15
	Percentile	0.01	99.1	0.90	200.15	49.58	-100.15
	Max BPAC	0.39	61.26	38.74	39.64	0.21	60.36

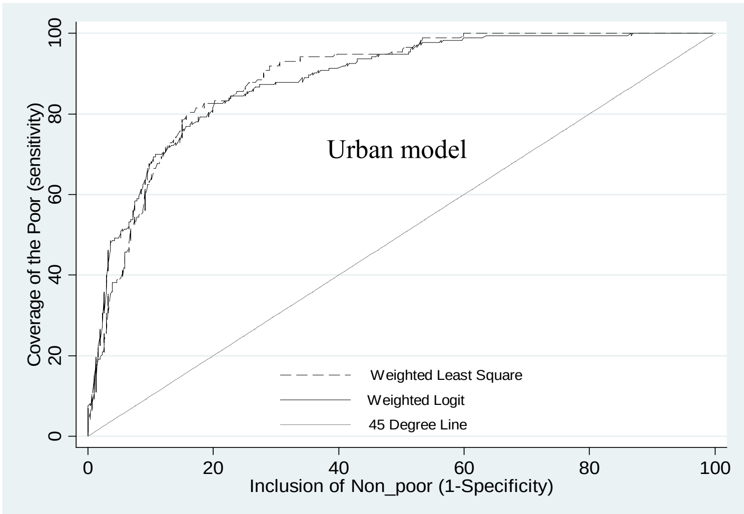
Source: Own results based on Malawi IHS2 data.



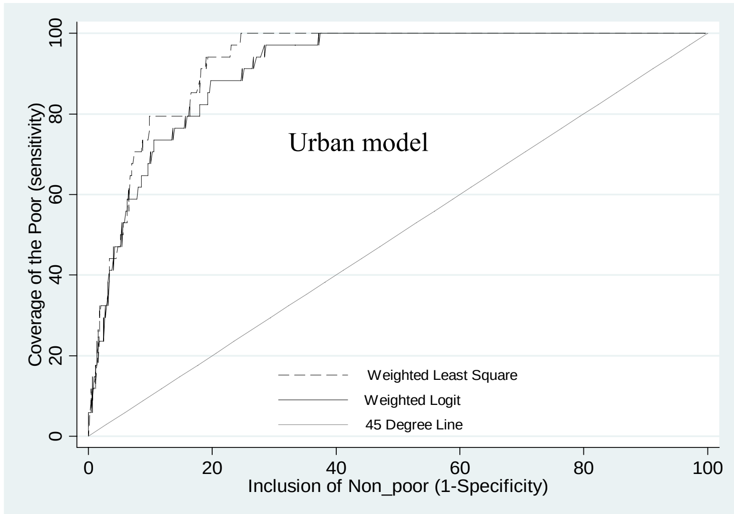
Annex 6: ROC curves of the rural model (international line)
Source: Own results based on Malawi IHS2 data.



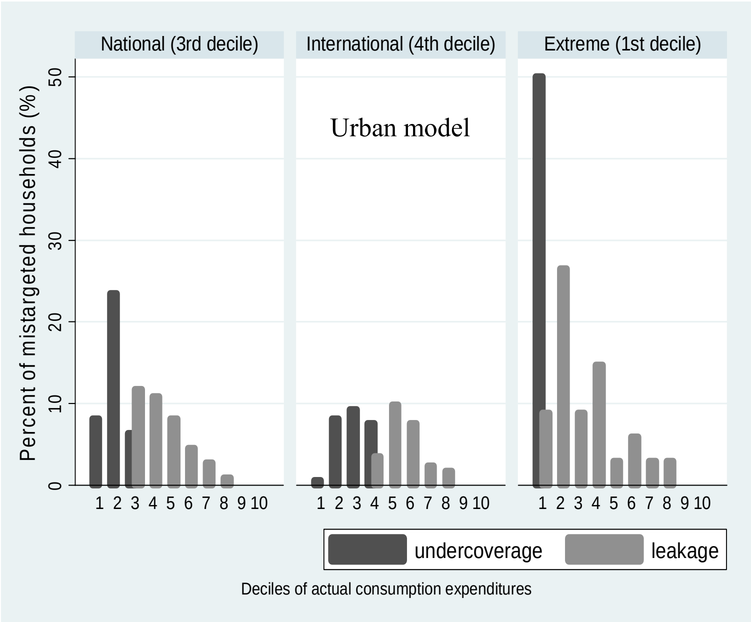
Annex 7: ROC curves of the rural model (extreme line)
Source: Own results based on Malawi IHS2 data.



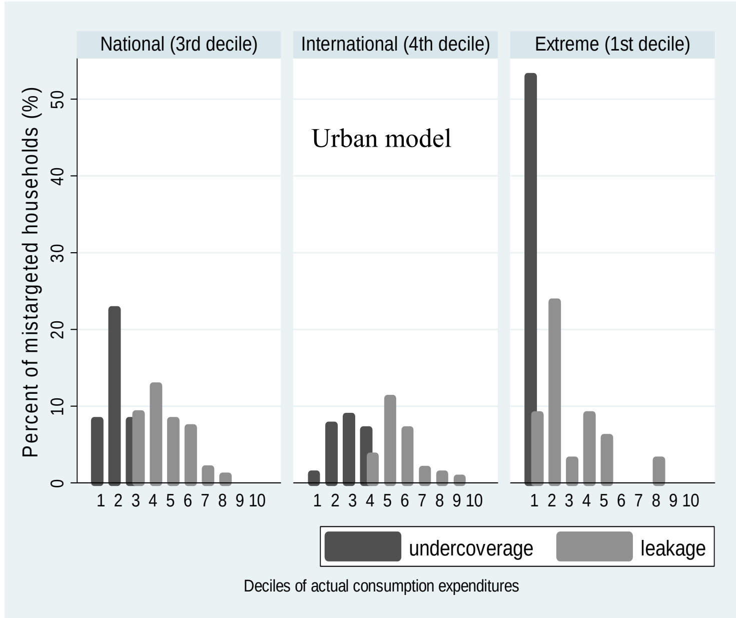
Annex 8: ROC curves of the urban model (international line)
Source: Own results based on Malawi IHS2 data.



Annex 9: ROC curves of the urban model (extreme line)
Source: Own results based on Malawi IHS2 data.



Annex 10: Targeting error distribution by poverty lines (WLS)
Source: Own results based on Malawi IHS2 data.



Annex 11: Targeting error distribution by poverty lines (WL)
Source: Own results based on Malawi IHS2 data.

CHAPTER III

TARGETING THE POOR AND SMALLHOLDER FARMERS

Empirical evidence from Malawi

Nazaire Houssou and Manfred Zeller

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Forthcoming in the Quarterly Journal of International Agriculture

Abstract

This paper develops low cost, reasonably accurate, and simple models for improving the targeting efficiency of development policies in Malawi. Using a stepwise logistic regression along with other techniques applied in credit scoring, the research identifies a set of easily observable and verifiable indicators for correctly predicting whether a household is poor or not, based on the 2004-05 Malawi Integrated Household Survey data. The predictive power of the models is assessed using out-of-sample validation tests and receiver operating characteristic curves, whereas the model robustness is evaluated by bootstrap simulation methods. Finally, sensitivity analyses are performed using the international and extreme poverty lines.

The models developed have proven their validity in an independent sample derived from the same population. Findings suggest that the rural model when calibrated to the national poverty line correctly predicts the status of about 69% of poor households when applied to an independent subset of surveyed households, whereas the urban model correctly identifies 64% of poor. Increasing the poverty line improves model targeting performances, while reducing the poverty line does the opposite. In terms of robustness, the rural model yields a more robust result with a prediction margin of ±10% points compared to the urban model. While the best indicator sets can potentially yield a sizable impact on poverty if used

in combination with a direct transfer program, some non-poor would also be targeted as the result of model leakage. One major feature of the models is that household score can be easily and quickly computed on the field. Overall, the models developed can be potential policy tools for Malawi.

Keywords: *Malawi, poverty targeting, proxy means tests, out-of-sample tests, bootstrap.*

CHAPTER IV

To TARGET OR NOT TO TARGET?

The costs, benefits, and impacts of indicator-based targeting

Nazaire Houssou and Manfred Zeller

A shorter version of this paper has been submitted to Food Policy Journal

Abstract

This paper assesses the cost-effectiveness of indicator-based targeting. Using household survey data from Malawi, we examine whether an indicator-based targeting of the poor is more cost-efficient in alleviating poverty than universal systems that broadly target the population. Furthermore, we assess whether a proxy indicator system is more target- and cost-efficient than past agricultural subsidy programs which used community-based targeting to deliver benefits to the poor and smallholder farmers in the country.

There is compelling evidence in favor of targeting Malawi's poor and smallholder farmers by proxy means tests because targeting benefits outweigh its costs. Targeting not only reduces the Malawian Government's direct costs, but also reduces overall program costs. Even though administrative costs increase under finer targeting, simulation results suggest that it does not make a targeted program cost-ineffective. Furthermore, finer targeting is found to have a stronger impact on poverty than universal coverage of the population. More importantly, the newly designed proxy system appears to be more target- and cost-efficient than the 2000/2001 Starter Pack and the 2006/2007 Agricultural Input Support Program (AISP). While the Starter Pack and the AISP transferred about 50% of total transfer, under the new system about 73% of transfer are delivered to the poor and smallholder farmers. Likewise,

under the new proxy system the costs of leakage are cut down by more than 50% compared to previous agricultural subsidy programs.

This work is prospectively relevant for Malawi as its policy makers reflect on improving the efficiency of the country's pro-poor development programs. Given the constraint in fiscal and donor resources, the sheer number of poor, and the competing development needs in the country, the savings from targeting can be used to expand program outreach or promote other pro-poor development policies. Finally, the research could be applied in other developing countries with similar targeting problems.

Keywords: *Malawi, poverty targeting, out-of-sample tests, redistribution, cost-effectiveness, cash transfers, agricultural subsidy, safety nets.*

1. Introduction

Malawi is one of the poorest countries in the world with a poverty rate of 52.4% (National Statistics Office - NSO -, 2005a). In response to endemic poverty, poor harvest, severe food insecurity, and unfavorable weather conditions, successive development programs, including fertilizer subsidy schemes were devised and targeted at the poor and smallholder farmers in the country. One such program is the Starter Pack Initiative (SPI) of 2000/2001 which provided free fertilizer and seeds to poor farmers at a total cost of about US$11 million (Smith, 2001). Similarly, the Agricultural Input Support Programs (AISPs) of 2005/2006 and 2006/2007 disbursed about 310,803 tons of subsidized fertilizer and seeds to poor farmers at a total cost of MK17.5 billion (Dorward et *al.*, 2008). Preliminary assessments suggest that the AISPs have improved the household food security and led to an increase of the country's national maize output with some of parts of the production being exported to neighboring countries (Dorward et *al.*, 2008; Minde et *al.*, 2008).

Input subsidy and other development programs in Malawi mostly rely on community-based targeting mechanisms in which local authorities and community representatives identify program beneficiaries based on their assessment of the household living standards. However, most of these programs display a poor targeting efficiency due to a number of factors, including various local perceptions, favoritism, abuse, lack of understanding of targeting criteria, political interests, etc. According to the IHS2 survey data, about 35% of rural poor did not benefit from the SPI, while 62% of non-poor did benefit the program. Likewise, an evaluation of the 2006/2007 AISP program by Dorward et *al.* (2008) suggests that 46% of the poor did not receive fertilizer vouchers, whereas 54% of non-poor wrongly received vouchers. Furthermore, a research by Ricker-Gilbert and Jayne (2009), suggests that the 2006/2007 AISP program has been targeted to wealthier and politically connected farmers who would otherwise have purchased the fertilizer, causing substantial displacement of commercial fertilizer estimated at about 30% to 40% on the market (Dorward et *al.*, 2008).

Better targeting has become an imperative for developing countries in the wake of macroeconomic and structural adjustment programs under which governments are pressured to cut back enormously on their expenditures (Chinsinga, 2005). Likewise, with a per capita income of US$230 (World Bank, 2008) and limited donor funds, the surplus available to redistribute is relatively small. Under these conditions, the first challenge for Malawi is to develop a low cost, fairly accurate, and easy system to target the poor and smallholder farmers. The second challenge is to assess whether targeting using such a system is more cost- and impact-effective compared to universal interventions and the currently used targeting mechanisms in the country.

This research seeks to address these challenges. We propose an alternative system that might improve the targeting efficiency of development programs and foster pro-poor economic growth, food security, and poverty reduction in Malawi. Furthermore, we estimate the costs, benefits, and poverty impacts of an indicator-based targeting and assess whether the newly developed system is more cost-efficient compared to the 2000/2001 SPI and the 2006/2007 AISP which used community-based targeting mechanism to deliver benefits to the poor and smallholder farmers.

There is compelling evidence in favor of targeting since considering all costs does not make a targeted program cost- and impact-ineffective. Likewise, the newly designed system appears to be more target- and cost-efficient than the 2000/2001 SPI and the 2006/2007 AISP. This piece of work is prospectively relevant for Malawi as its policy makers reflect on improving the efficiency of the country's pro-poor development programs. Likewise, the research could be applied in other developing countries with similar targeting problems. The paper is organized as follows. Section 2 discusses the targeting of development policies within the context of Malawi.

Section 3 reviews the principles of targeting. Section 4 sets out the methodology, whereas section 5 presents the results. Section 6 offers our concluding remarks.

2. Targeting Development Programs: The Malawian context

Deeply entrenched poverty is a major obstacle to Malawi's economic growth and development. The country is mostly agricultural with more than 85% of its population living in rural areas (NSO, 2005a) and about 90% of its households working in the agricultural sector. Almost half of the households are subsistence farmers. The agricultural sector contributed about 34% to the Gross Domestic Product in 2007 (World Bank, 2009a) and accounted for more than 80% of export earnings (World Bank, 2009b). With improved macroeconomic management, favorable weather conditions, and a supportive donor environment, in the last 3-4 years, the country has experienced high growth rates averaging 7.5% and the growth rate is projected at 6.9% in 2009 (World Bank, 2009b).

Historically, there has been no coherent strategy for targeting the poor and vulnerable in Malawi (Smith, 2001). There exist a large number of targeted programs in the country, most of which are uncoordinated short-term relief or emergency responses. In the period 2003-2006, including emergency aid and disaster response, the combined safety nets/social protection system amounted to an average of more than US$134 million per year; that is about 6.5% of the country's Gross Domestic Product (World Bank, 2007).

Fertilizer subsidy has been a key element of the Malawian Government's present policy (World Bank, 2007). The provision of agricultural inputs, especially fertilizer, enjoys a special place in the popular hierarchy of anti-poverty measures in Malawi (Smith, 2001). For instance, the SPI of 1998/1999 provided 10 kilograms (kg) of fertilizer, along with seeds to all smallholder households at a cost of US$27 million. But, confronted with the fiscal burden, the Government subsequently scaled down the program to a targeted version and funding has been therefore substantially reduced. In 2005/2006 growing season, a new fertilizer subsidy program was devised in the country following an extremely poor harvest in 2004/2005. The program which cost about US$33 million (Ricker-Gilbert and Jayne, 2009), was scaled up in the following year. According to NSO's estimates, the 2006/2007 AISP program provided fertilizer and seeds to just under 2.5 million rural households (Dorward et *al.*, 2008) and cost about US$91 million. The program distributes about 3.482 million of fertilizer coupons with which each qualified farming household is entitled to purchase 1 bag of 50 kg of Urea and 1 bag of 50 kg of NPK at a subsidized rate of MK950 or approximately 28% of market price. Though the AISP planned to provide farmers with two coupons (one coupon for basal dressing and one for top dressing of the soil), some farmers were given only one coupon and were imposed either of the fertilizer type. Likewise, 28% of the coupons were unaccounted for. As in most previous programs, the AISP was implemented through a community-based targeting mechanism in which local authorities and other community representatives select program beneficiaries based on their assessment of household living conditions. However, almost all development interventions have targeting problems in the country (Government of Malawi and World Bank, 2007): they cover a limited number of poor and leak program benefits to a significant number of non-poor. To put this in perspective, we estimate in Table 1, the targeting efficiency of selected programs as measured by their undercoverage and leakage rates.

Table 1. Targeting efficiency of Malawi's development programs

Program type	**Undercoverage** (%)	**Leakage** (%)
Free food distribution	70.99	31.23
Input-for-work	98.61	0
Starter Pack (rainy season)[1]	34.98	61.81
Starter Pack (dry season)[1]	94.96	8.03
Food/cash-for-work	93.06	6.19
ILTPWP[2]	72.9	2.6
AISP[3]	46	54
Average performance	73.07	23.41

Source: Own results based on Malawi IHS2 data. [1]Results based on rural areas only. [2]Excerpts from World Bank (2006) and [3]Dorward et *al.* (2008). AISP denotes Agricultural Input Support Program. The Improved Livelihood Through Public Works Programs (ILTPWP) was implemented in six districts of the central region of Malawi.

Table 1 suggests that Malawi's development programs are badly targeted, with average undercoverage and leakage estimated at about 73% and 23%, respectively. The results are consistent with World Bank (2007) which reports that the level of funding for different programs in the country is not necessarily inadequate, but many programs do suffer from limited beneficiary coverage, mis-targeting, and significant leakages to the non-poor. Likewise, most of them are too small in scale to have a meaningful impact. Clearly, under the community-based targeting system, development programs are not reaching their intended beneficiaries and therefore, they are unlikely to yield their intended effects on poverty and economic development in the country. To reverse this trend, we propose targeting by proxy means tests which if well implemented could considerably improve the efficiency of the country's development programs.

3. The Principles of Targeting: A theoretical perspective[20]

The principles of targeting are well established in the literature. However, less is known about the costs of targeting. By definition, targeting is the process by which benefits are channelled to the members of the high priority group that a program aims to serve (Grosh and Baker, 1995). It is a means identifying which members of society should receive a particular benefit (Rook and Freeland, 2006). It involves two elements: first defining who should receive benefits and second establishing mechanisms for identifying those people[21].

From a welfare point of view, targeting should address institutional failures (market failures) and distributional issues regarding access to assets, services, inputs for production or human capital formation and maintenance. The case for narrow targeting rests on the existence of a budget constraint (Coady et *al.*, 2004). Since the public budget is scarce, ideally targeting should help direct transfers or services or improve access as much as possible to/for those who need them most. Targeting should not be only seen as an effort to improve the immediate

[20] A substantial part of this section is inspired from Besley and Kanbur (1993).
[21] See below for a brief survey of these mechanisms.

consumption of the poor, but also as an investment in the future by ensuring the productivity of the next generation and long term economic growth. It is a pro-poor development strategy since it reduces the leakage of scarce public resources to people who do not need assistance.

However, targeting is not costless. It imposes administrative costs that reduce the amount of benefits available for the actual intervention (Hoddinott, 1999). Likewise, no feasible targeting mechanism is perfect; all available options involve two types of errors: undercoverage and leakage. Undercoverage represents a failure of the program to cover all poor. Leakage is an error of including non-poor as program beneficiaries. While effective targeting may reduce the government's direct costs for providing benefits, it does not necessarily reduce the total costs of a targeted program (Rook and Freeland, 2006; Dutrey, 2007).

Targeting entails a number of costs. These include the costs of transfer to the poor, the costs of leakage to the non-poor, administrative costs, and the hidden costs of targeting which comprise: private, indirect, social, and political costs[22]. The *transfer* to the poor is the amount of benefits that reach effectively the poor who are the intended program beneficiaries. The *leakage* is the amount of benefits that is wrongly given to the non-poor. The transfer to the poor is a good use of resources, whereas leakage to the non-poor is a waste of resources although it may increase political support for targeting[23]. *Administrative costs* include the costs of data collection for developing a targeting algorithm (e.g. developing a proxy means test model), the cost of regular screening of program beneficiaries, the costs of processing and delivering program benefits, and program staff costs.

P*rivate costs* consist of costs, such as income lost (e.g. opportunity cost of participating in a targeted intervention), the time, and fees necessary for the poor to prove their eligibility for targeted benefits. *Indirect costs* or incentives costs arise when for example

[22] See Rook and Freeland (2006); Coady al, (2002), and van de Walle (1998) for a fuller description of targeting costs and benefits.

[23] See for example Gelbach and Prichett (2000) for a discussion on the political economy of targeting.

beneficiaries report faulty information in order to qualify for a transfer scheme. This is likely the case when targeting criteria are not explicit and verifiable or in the absence of an effective verification process. *Social costs* arise from the stigma associated with declaring oneself as poor, the deterioration of community cohesion due to selective targeting, and the erosion of informal support networks.

Political costs arise from the fact that politicians can manipulate or abuse targeting rules in order to favor their constituencies and garner political support. In addition, targeting can erode the political support from the wealthier, especially if it is financed through the taxation of non-poor. On the other hand, targeting may increase political support from those who support it based on its indirect benefits to them – e.g. feeling of social justice or being hassled by fewer beggars, and security – (Coady et *al.*, 2002). To our knowledge, there is no comprehensive study on the hidden costs of targeting in the literature.

The total cost of targeting depends on a number of factors, including population coverage, targeting method, implementation mechanisms, socio-political environment, etc. Though less is known about the costs of targeting, it is generally agreed that the finer the targeting, the higher the administrative and hidden costs. The following diagram shows administrative and hidden costs of targeting as a function of population coverage.

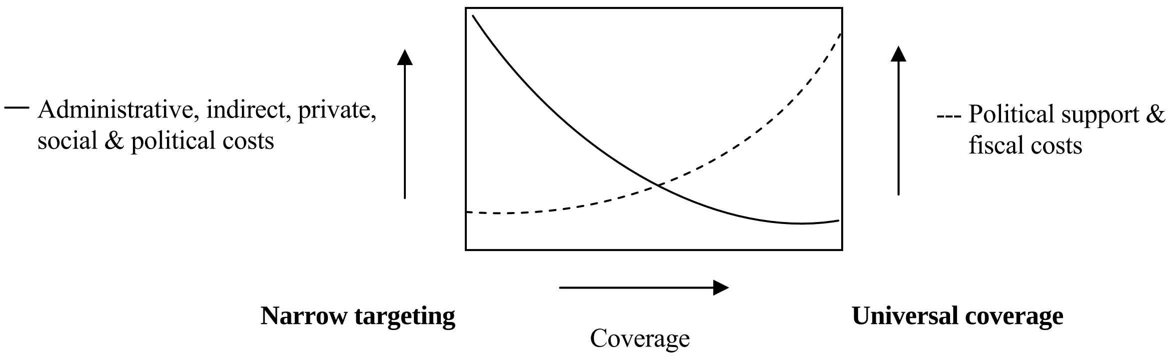

Figure 1: Costs of targeting.
Source: Adapted from Smith (2001).

Figure 1 suggests that narrow targeting (of the poor) increases administrative, indirect, private, social, and political costs and reduces fiscal costs. As the coverage of the population increases toward universal coverage, administrative, indirect, private, social, and political costs fall, whereas political support improves, but fiscal costs increase due to excessive leakage to non-poor.

Related to narrow targeting is the so-called "*ideal solution*" for targeting a transfer scheme (Besley and Kanbur, 1993). The ideal solution implies a perfect targeting and complete elimination of poverty. It supposes that income or expenditures can be observed accurately and costlessly, and no incentive effects prevent the state from plugging the gap between poverty line and income. The ideal solution is depicted in the panel to the left of Figure 2, which plots the final (i.e. post transfer) against the original income.

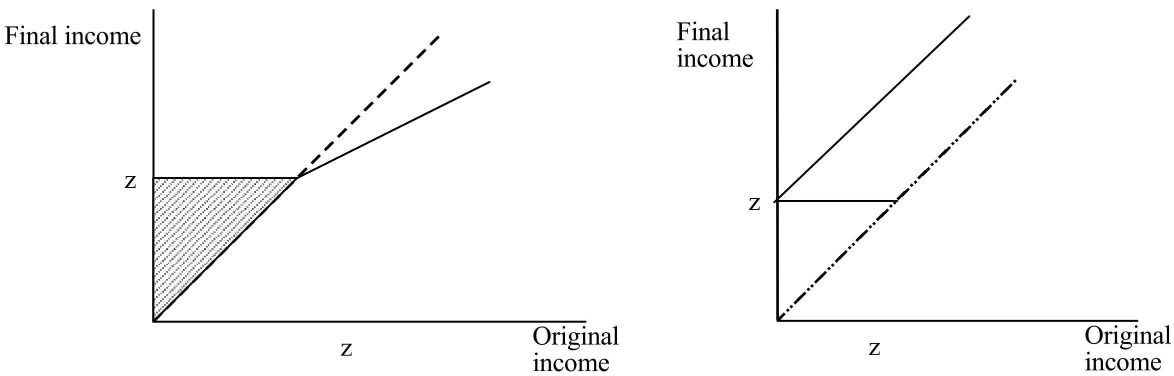

Figure 2: Ideal solution (left) and universal coverage (right) for targeting a transfer scheme.
Source: Besley and Kanbur (1993).

Along the dotted 45° line, there is no difference between original and final income. A point above this line indicates a subsidy or transfer, while a point below indicates a withdrawal or tax. The ideal solution is given by the solid line. For anybody with original income y less than z, the government transfers exactly the amount z-y so as to bring final income up to z. This completely eliminates poverty. The financial cost of this strategy is given by the sum of these transfers z-y. If the distribution of income is uniform, then this cost would simply be depicted by the triangular areas between the horizontal solid line and the 45° line. The structure of the scheme for those with income above z depends on the nature of the budget constraint. If the transfer scheme is to be self-financing, then those with incomes above z have to be taxed. This is shown by the solid line beyond z, but below the 45° line. The larger the tax revenue to be raised, the shallower this line will have to be in order to balance the budget. If the state is perfectly informed, the ideal solution is clearly the least cost method of alleviating poverty. It relies on being able to transfer the right amount to each individual below the poverty line without affecting their incentives to earn.

Opposite to the ideal solution for targeting is universal coverage. A universal scheme gives everybody a transfer of z independently from its income level. This is depicted by the panel to the right of Figure 2. This scheme also eliminates poverty, but at a far greater budgetary cost. Everyone, even someone with original income exceeding z, receives a transfer of z from the government. The budgetary cost is just z times the population size. If the scheme is to be financed through taxation, then the marginal tax rates on non-poor will need to be higher than in the ideal solution.

The main question is: are both extreme feasible (Besley and Kanbur, 1993)? The ideal solution is not feasible for three main factors: the costs of administration, individual responses and incentive effects, and considerations of political economy. The administrative costs involved in the ideal solution are high; its quantification is not an easy task. Besides, the ideal solution implies a means testing based on a regular measurement of individual or household income. It is very difficult to assess and verify income, even in developed countries.

Furthermore, the ideal solution imposes a higher marginal tax rate on the poor than on non-poor. If the original income of the poor is zero, then the marginal tax rate on the rich will have to be higher than that indicated by the ideal solution[24]. In both cases, the marginal tax rates might affect incentives to work and hence income. This will be reflected in the political and indirect costs of the program. On the other hand, a universal scheme will have a medium level

[24] From the theoretical point of view, higher marginal tax rate on the rich is justified by the law of declining marginal utility.

marginal tax rate on everybody. However, empirical evidence is limited as to which level of tax rate to impose upon the society (Besley and Kanbur, 1993). Likewise, individual costs (e.g. social and private costs) of participating in a finely targeted program meant specifically for the poor might deter them from joining the program. The alternative is to have a universal scheme which gives everyone the same amount of transfer, but universal scheme is costly and does not do much for the poorest. Indeed, many countries began to switch from universal to targeted programs (Smith and Subbarao, 2003).

In addition, the ideal solution might not enjoy enough political support to predominate since is it targeted only to the poor who often lack sufficient political power. A finely targeted program may be divisive, exacerbates social tensions, and further isolates the poor. Likewise, politicians can manipulate targeting rules for their own interest. Conversely, universal coverage has the advantage of covering non-poor as well, thus increases political support for a transfer scheme.

In theory, none of the above solutions is feasible. The alternative is to consider an *intermediate solution* which lie somewhere in the middle of the curves (Figure 1). This solution is based on various targeting mechanisms, including indicator-based targeting methods (proxy means targeting, categorical targeting), community-based targeting, geographical targeting, self-targeting, and subjective self-assessment[25]. All of these methods have the same goal: to correctly identify which households are poor and which are not. However, none of them is perfect at targeting. Most often, they exhibit a trade-off between accuracy and practicality/costs of implementation as shown in Figure 3.

[25] See Coady et *al.*, (2002); Conning and Kevane (2002), and Grosh and Baker (1995) for a fuller description of targeting methods.

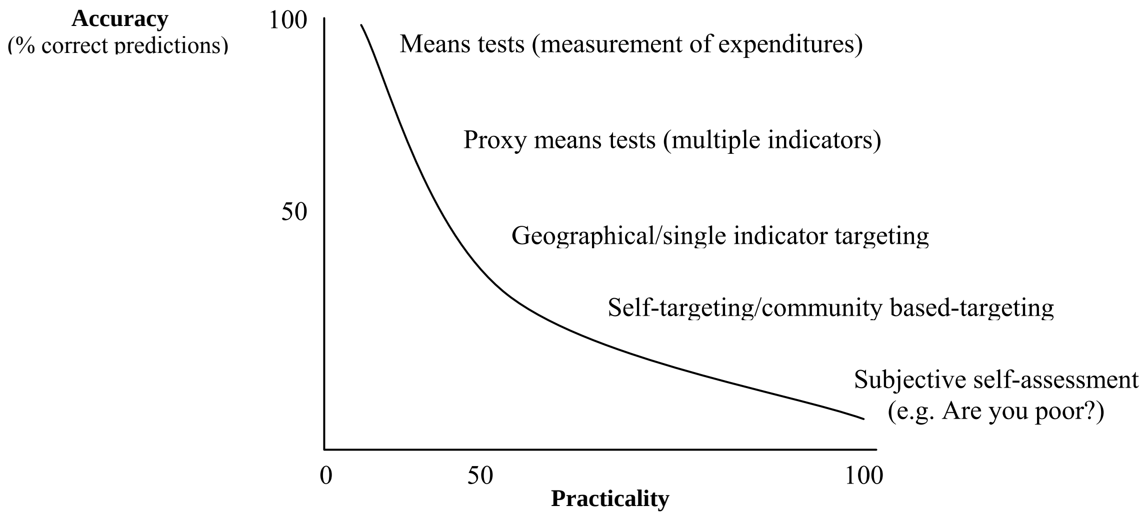

Figure 3: Trade-off between practicality and accuracy.
Source: Own conception.

Figure 3 shows that the higher the method accuracy, the lower the practicality (or the higher the costs of implementation) and vice versa. Means tests are the best way of determining eligibility[26]. They are highly accurate (assuming the information provided by the household is free from error) since they rely directly on income or consumption. However, they are unpractical and very expensive to implement, especially in developing countries. Geographical and single indicator targeting are more practical, but they are less accurate than means tests. On the other hand, subjective self-assessment is the most practical method, but it is poorly accurate. Conversely, proxy means tests are more accurate than geographical targeting, single indicator targeting and subjective self-assessment. Besides, they are more practical than means tests.

Compared to most targeting methods, proxy means tests have the merit of making replicable judgments using consistent and visible criteria (Coady et *al.*, 2002). They are also simple to implement and less costly than sophisticated means tests. For example, in a recent review of 122 targeted anti-poverty interventions, Coady et *al.* (2004) found that proxy means tests show good results on average, even though there is a wide variation in targeting performances between programs. Likewise, Coady and Parker (2009) found that administrative

[26] Means tests directly measure household income to determine its welfare level. Because of the difficulties associated with such tests, they are largely reserved for industrialized countries. See Coady et *al.* (2002) and Grosh and Baker (1995) for further details on means tests.

selection based on proxy means testing is particularly effective at reducing overall program coverage while maintaining high coverage of the lowest welfare households. Therefore, we propose targeting by proxy means tests as a mechanism to target the poor and smallholder farmers in Malawi. Proxy means tests use household socioeconomic indicators to proxy household income or welfare level. In general, the aim is to find one or a few indicators which are less costly to verify, but are sufficiently correlated with income or expenditures to be useful for poverty alleviation (Besley and Kanbur, 1993). The advantage of using few indicators is that administrative costs are kept low, while leakage is less than what it would be under universalistic scheme, so that more poverty reduction could be achieved with the same budget.

The total budget required for targeting a transfer scheme can be formulated as follows (Besley and Kanbur, 1993):

$$T = P + NP + A + H$$

Where:
T is the total budget of the program;
P is the value of transfers given to the poor;
NP is the value of transfers wrongly given to non-poor;
A is the administrative costs;
H is the hidden costs (private, indirect, social, and political costs).

A measure of the targeting efficiency is given by:

$$F = P*100/(P + NP)$$

Alternative measures of targeting efficiency include:

$$F_1 = (NP + A + H)/P$$

$$F_2 = P*100/(P + NP + A + H)$$

F is defined as the transfer to the poor as a percentage of total transfer;
F_1 is the cost of transferring one unit of resources to the poor;
F_2 is defined as the transfer to the poor as a percentage of total program cost.

Administrative costs as a function of the total program cost are given by:

$$C = A/(P + NP + A + H).$$

Following Besley and Kanbur (1993), we hypothesize that C rises with F at an increasing rate. Figure 4 shows administrative costs as a function of program efficiency.

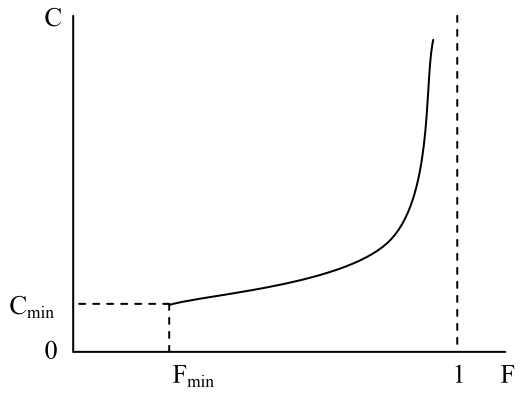

Figure 4: Administrative cost function.
Source: Besley and Kanbur (1993).

Figure 4 shows that there is a minimum level of costs (C_{min}) for any development policy or program whether randomly or universally targeted. Associated with that is a minimum transfer efficiency (F_{min}) which is always achievable under any program. Furthermore, the higher the targeting efficiency, the higher the administrative costs. Compared to the ideal solution, universal coverage has lower administrative costs, but higher overall program costs. Since less is known about the exact shape of the curve, the quantification of administrative costs is often approximated. In the literature, these costs range from 0.1% to 30% of total program cost (see Grosh and Baker, 1995; Smith, 2001; Coady, 2003; Smith and Subbarao, 2003).

4. Data and Methodology

4.1 Data

This research used the Malawi Second Integrated Household Survey (IHS2) data of 2005. The NSO (2005b) conducted the IHS2 with the assistance of the International Food Policy Research Institute (IFPRI) and the World Bank[27]. The IHS2 which was carried out from March 2004 through March 2005 covered a nationally representative sample of 11,280

[27] We gratefully acknowledge the NSO for providing us with the data.

households that were selected based on a two-stage stratified sampling design. This design involved in the first stage the selection of primary sampling units based on Probability Proportional to Size (PPS) sampling and in the second stage a random selection of surveyed households. Likewise, the survey covered a wide range of socioeconomic indicators, including household consumption expenditures.

We define poverty in this research as a level of consumption and expenditures which has been calculated to be insufficient to meet individual basic needs in a household. This definition is a standard but narrow view of poverty (Benson, 2002). It does not consider the capability of individuals to achieve a desired life as conceptualized by Sen (1987). However, in view of the widespread use of monetary poverty lines with expenditure-based measures of poverty, this research pursues a policy-relevant objective by identifying indicator-based tools that can simplify the identification of rural poor and measure welfare changes over time in poor populations.

4.2 Estimating the models

4.2.1 Estimation method

Separate models were estimated for rural and urban households due to substantial differences between rural and urban areas. These models were estimated using the quantile regression. Previous applications of quantile regression for poverty targeting include Braithwaite et *al.* (2000), Zeller and Alcaraz V. (2005), Zeller et *al.* (2005), and Muller and Bibi, (2008). Quantile regression was first introduced by Koenker and Bassett (Koenker and Hallock, 2001). Defined in the simplest way, quantile regression is a statistical procedure intended to estimate conditional quantile functions in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates. In analogy with classical linear regression methods (e. g. ordinary least squares), based on minimizing sums of squared residuals and meant to estimate models for conditionals mean functions, quantile regression methods are based on minimizing asymmetrically weighted absolute residuals and intended to estimate conditional median functions.

The quantile regression was deemed appropriate for estimating the models because we are interested in a particular segment (i.e. the poor) of the analyzed conditional distribution (here the welfare distribution) as a function of several covariates of interest. Furthermore, quantile regression does not impose any sort of strict parametric assumptions on the analyzed distribution. The general form of the model takes the following form:

$$y_i = \beta_j x_{ij} + \varepsilon_i$$

where y_i is the dependent variable, i.e. the logarithm of daily per capita expenditures;
x_{ij} is a set of poverty predictors;
β_j is a vector of parameter estimates;
ε_i is the random error term.

The minimization problem is formulated as follows:

$$\min \sum \rho_\tau \left(y_i - \xi \left(x_{ij}, \beta_j \right) \right)$$

where ρ_τ is a tilted absolute value function with the τ^{th} sample quantile as solution.
$\xi\left(x_{ij}, \beta_j\right)$ is a parametric function that can be formulated as linear.

The simplex algorithm was used for solving the minimization problem (SAS Institute, 2006). A model with a high explanatory power is a prerequisite for good predictions of the dependent variable per capita daily expenditures (and thereby poverty status). Initially the set of predictors included 148 practical indicators that where selected to ensure an operational use of the models[28]. These indicators were selected based on Zeller et *al.* (2006) and included practicability considerations regarding the ease and accuracy with which information on the indicators could be quickly elicited in an interview as well as considerations regarding the

[28] The list of indicators was reduced to 112 for the urban model; some of the variables were not relevant in urban areas.

objectiveness and verifiability of an indicator[29]. The list of selected indicators was then submitted to stepwise regressions out of which the best ten indicators with highly significant coefficients (at an error level of 1% or less) were retained[30]. To reflect the importance of each household, the regression was weighted by the household weight in the population. In addition, we controlled for agricultural development districts in the rural model and the four major cities: Mzuzu, Zomba, Lilongwe, and Blantyre in the urban model.

Since we are particularly interested in identifying accurately the poor, we estimated the quantile regression at the point of estimation that corresponds to the poverty rate in the population. In that way, the estimation can be said to focus on the poor. The models developed do not seek to identify the determinants of poverty, but select variables that can best predict the current poverty status of a household[31]**.** A causal relationship should not be inferred from the results.

4.2.2 Out-of-sample tests

Out-of-sample validation tests were conducted to assess the predictive power of the models. The main purpose of the validations is to observe how well the models perform in an independent sample derived from the same population. In order to perform the tests, the initial samples were first split into two sub-samples following the ratio 67:33. The larger samples or *calibration samples* were employed to estimate the models i.e. identify the best set of variables, their weights, and the optimal cut-offs, whereas the smaller samples or *validation samples* were used to test out-of-sample the predictive accuracy of the models. In the out-of-sample tests, we therefore applied the set of identified indicators, their weights and the

[29] In addition, before estimating the regressions, the list of selected variables was further screened for multicollinearity.
[30] Previous researches (Zeller and Alcaraz V., 2005 and Zeller et al., 2005) show that in general, the higher the number of indicators, the higher the prediction accuracy and the lower the model practicality (higher cost of data collection). In this paper, we used the best ten indicators in order to balance the model accuracy and practicality or operational use.
[31] See for example Sen (1984) for a conceptual framework on poverty and Mukherjee and Benson (2006) for a study on the determinants of poverty in Malawi.

optimal cut-offs to predict the household poverty status. Furthermore, the model robustness was assessed by estimating the prediction intervals of the targeting ratios using 1, 000 bootstrapped resamples[32].

In the selection of the calibration samples, we followed a two-stage stratified sampling selection process and PPS protocol in order to mimic the initial sample selection. This design ensures that all strata are adequately represented in the model estimation. In order, to confirm the representativity of the calibration samples, we tested the differences in estimates between the samples and the full datasets. The results of the tests show no statistically significant difference between both sets. Therefore, the calibration samples are as representative as the full datasets. Table 2 describes the sample size and the number of indicators by model types.

Table 2. Sample size by model types

Sub-samples	Rural model	Urban model	Total
Total sample size	9,840	1,440	11,280
- *calibration (2/3)*	6,560	960	7,540
- *validation (1/3)*	3,280	480	3,760
Number of indicators	148	112	-

Source: Own calculations based on Malawi IHS2 data.

[32] See Efron (1987) for further details on bootstrapped simulation methods.

4.2.3 Measuring targeting performances

Different performance measures can be used to assess the targeting performances of a poverty assessment model (Table 3).

Table 3. Selected accuracy ratios

Targeting ratios	Definitions
Poverty Accuracy	Number of households correctly predicted as poor, expressed as a percentage of the total number of poor
Undercoverage	Number of poor households predicted as non-poor, expressed as a percentage of the total number of poor
Leakage	Number of non-poor households predicted as poor, expressed as a percentage of the total number of poor
Poverty Incidence Error (PIE)	Difference between predicted and actual poverty incidence, measured in percentage points
Balanced Poverty Accuracy Criterion (BPAC)	Poverty accuracy minus the absolute difference between undercoverage and leakage, measured in percentage points

Source: Adapted from IRIS (2005) and Houssou and Zeller (2009)

Having estimated the models, the question arises as to what cut-off to use to predict the household poverty status. Therefore, the cut-offs that maximized the BPAC after calibrations were used. Households with predicted expenditures higher than these cut-offs were predicted as poor, otherwise they were deemed non-poor. This classification was then crossed with the actual household poverty status. The latter is defined as follows: households with expenditures less than the national poverty line (MK44.29 a day) were classified as poor, otherwise they were deemed non-poor. Finally, we calibrated the models to the international and extreme poverty lines as different development institutions might be interested in targeting different poverty groups in the population.

4.3 Methodology for the simulations

It is often argued that targeting is cost-ineffective and once all targeting costs have been considered, a finely targeted program may not be any more cost-efficient and may not have any more effect on poverty than a universal program. Therefore, an evaluation of the costs and benefits of targeting was performed under the new system and a program which provides cash transfer to the poor. Likewise, we assess whether the new system is more target- and cost-efficient than community-based targeting of agricultural subsidy programs.

In order to fit with the existing institutional capacity for handling a targeted program, we assumed a realistic transfer scheme to cover 20% of the population; that is approximately equivalent to the proportion of direct beneficiaries of under the initial version of the SPI[33]. Likewise, we set the total annual budget available for targeting the rural population at US$30 million. This amount is approximately equivalent to the total cost of the initial version of SPI and corresponds to about one-third of the costs of the AISP in 2006/2007. It represents just about 9% of the Government's annual expenditures on public work programs in 2000 and 1% of Malawi's GDP in 2005[34]. Under the urban model, the total budget available for targeting was set at 10% of the budget allocated for targeting the rural poor (i.e. US$3 million). This rate is roughly proportional to the number of urban poor. Both budgets were exogenously determined; we did not consider financing the redistribution through the taxation of non-poor.

We simulated three transfer schemes and evaluated their costs, benefits, and poverty impacts based on the model targeting performances[35]. The first scheme provides a fixed amount of transfer to all poor irrespective of their poverty level, whereas the second scheme grants transfer to the poor progressively according to their level of consumption. In other words, the second scheme provides the poorest with the exact transfer needed to bring them up to the poverty line. This redistribution scheme was implemented progressively starting from the poorest poor till the available budget (net of costs) is exhausted. The scheme aims at reducing extreme poverty and represents a finer targeting compared to the first scheme. We define the latter as *uniform targeting* and the former as *progressive targeting*. Uniform targeting is the scheme applied for providing fertilizer subsidies to program beneficiaries in Malawi.

[33] 20% coverage of the population is a policy variable that can be set at any government wishes.
[34] Malawi's GDP is estimated at US$2.9 billion in 2005 (World Bank, 2008).
[35] We based our simulations on the performances of the models calibrated to the national poverty line, but we conducted further simulations based on the international and extreme poverty lines.

However, both schemes do not respect the initial welfare ranking of the population. With the uniform scheme, the poor who are just below the poverty line would get richer than the non-poor who lie just over the line after transfer. Likewise, under a progressive targeting scheme individuals in the poorest deciles would get richer than the less poor. Therefore, a third scheme was implemented. The third scheme which is termed as *fair targeting*, not only covers all poor, but also respects the initial welfare ranking of the total population. Under this scheme, a poorer individual would not get richer than its less poor neighbor. Likewise, the less poor receive less transfer and the poorer receive more transfer. It is the finest redistribution scheme. We compared the benefits and costs of targeting with the reference point of *universal coverage*. Under the universal scheme, the available budget is distributed equally among the population covered by the program. The universal scheme assumes that there is no targeting.

With respect to administrative and hidden costs of targeting, they were set following Smith and Subbarao (2003), Smith (2001), and Besley and Kanbur (1993) who hypothesize that the finer the targeting, the higher the costs of administration[36]. Therefore, under the uniform scheme, administrative costs of targeting were estimated at 30% of the budget available for poverty reduction. In addition, we set the hidden costs of targeting at 5% of program administrative costs. Since progressive targeting is finer than uniform targeting, we further increased administrative costs to 35% of the program budget and the hidden costs to 10% of administrative costs in the second scheme. Under a fair targeting scheme, the costs are assumed to be identical to the costs under the second scheme, because both schemes provide transfers to the poor in similar fashion.

Under a universal coverage, we set administrative costs at 50% of the costs under uniform targeting. In other words, under a universal coverage administrative costs were set at 15% of total program cost. Likewise, we assumed that under a universal redistribution, the hidden costs of targeting are negligible because everyone is qualified for transfer in that case;

[36] Confer section 2.

no eligibility screening is required. Similarly, under the SPI and AISP programs, administrative costs were set at 15% of total program costs[37] and the hidden costs of targeting were estimated at 5% of administrative costs.

We estimated the impacts of targeting on poverty using the Foster-Greer-Thorbecke (FGT)[38] poverty index, which is defined as follows:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{z - y_i}{z}\right)^{\alpha}$$

where P_α is the poverty measure, N is the total population, z is the cut-off applied or generally the poverty line, q is the total number of poor, and y_i is the predicted household per capita consumption expenditures.

When $\alpha = 0$, the poverty measure P_0 is the incidence of poverty or the headcount ratio, that is the proportion of individuals whose expenditures is below the poverty line. With $\alpha = 1$, the relative importance given to all individuals below the poverty line is proportional to their expenditures and the poverty measure P_1 is the poverty gap measure. If $\alpha = 2$, then the poverty measure P_2 takes into account the degree of inequality among poor individuals, the depth of poverty as well as the number of poor. This poverty measure, also called the squared poverty gap is a measure of the severity of poverty.

Following Ravallion and Chao (1989), we estimated the benefits of targeting as the amount by which an untargeted budget would have to be increased in order to achieve the targeted poverty level. This amount is the budget difference between a universal coverage and a targeted program with the same poverty impacts. This assessment is, however static and underestimates the benefits of targeting. Targeting generates a number of benefits, the most obvious being the savings from excessive leakage to non-poor. Likewise, targeting benefits may percolate through and strengthen over time through the positive external effects of

[37] This rate is roughly equivalent to estimates by Dorward et *al.* (2008).
[38] See Foster, Greer, and Thorbecke (1984) for a detail description of the FGT index.

development on the poor (van de Walle, 1998). Measuring the full effects of targeting requires data that are beyond the scope of this research. Therefore, we limited the evaluation to the direct benefits of targeting.

5. Empirical Results

5.1 How well do the models predict the household poverty status?

Table 4 presents the model results calibrated to three poverty lines, including the prediction intervals. The poverty lines applied and the parameter estimates are presented in annex 1 thru 3. The parameter estimates are highly significant. Their signs are consistent with expectations and economic theory.

Table 4. Model targeting performances by poverty lines

Targeting ratios / **Poverty lines***	**Log cut-off value**	**Poverty accuracy** (%)	**Under-coverage** (%)	**Leakage** (%)	**PIE** (% points)	**BPAC** (% points)
Rural Model						
National	3.90	**71.48** (69.3; 73.6)	**28.52** (26.4; 30.7)	**26.65** (23.7; 29.6)	**-0.88** (-0.0; 0.8)	**69.61** (64.5; 72.9)
International	4.30	**80.38** (78.8; 82.1)	**19.62** (17.9; 21.2)	**16.92** (15.0; 18.8)	**-1.77** (-3.3; -0.1)	**77.69** (74.2; 81.4)
Extreme	3.30	**48.71** (45.2; 52.4)	**51.29** (47.6; 54.8)	**40.57** (35.4; 46.1)	**-2.41** (-4.0; -0.9)	**37.99** (29.6; 47.2)
Urban Model						
National	3.63	**60.36** (51.5; 69.2)	**39.64** (30.8; 48.5)	**48.65** (34.3; 67.3)	**2.08** (-1.9; 6.2)	**51.35** (32.7; 62.9)
International	4.06	**78.04** (71.8; 84.0)	**21.97** (16.0; 28.2)	**34.10** (24.2; 44.5)	**4.38** (-0.2; 8.1)	**65.90** (55.5 ; 74.9)
Extreme	2.93	**47.06** (29.1; 65)	**52.94** (35; 70.9)	**73.53** (40.5; 123.8)	**1.46** (-1.3; 4.2)	**26.47** (-22.8; 50.0)

Source: Own results based on Malawi IHS2 data. Prediction intervals in brackets. *See annex 1for description of poverty lines. Cut-offs values are expressed in Logarithm of Malawi Kwacha (MK).

Table 4 shows that the rural model yields a poverty accuracy of 71.48% and a BPAC of 69.61% points when calibrated to the national poverty line. This result indicates that the model would cover about 71% of the poor if used for targeting poverty. The model's undercoverage is estimated at about 28.52%, while its leakage is set at 26.65% which means that the model would leak program benefits to 27% of non-poor. The PIE nears 0% points, which implies that the model perfectly predicts the observed poverty rate out-of-sample.

Table 4 further indicates that raising the poverty line increases the BPAC and the coverage of the poor by about 10% and 7% points, respectively and reduces the leakage by about 10% points under the rural model. These results suggest a sizable improvement in the model's targeting performances with about 80% of the poor correctly targeted. On the other hand, reducing the poverty line disappointingly reduces the model's targeting performances. For instance, the model's poverty accuracy is reduced by 20% points, whereas its leakage increases by about 15% points.

With regard to the urban model, the same trend applies. However, the BPAC is lower (51.35% points) as compared to the rural model and only 60% of the poor are covered when the model is calibrated to the national poverty line. Besides, the leakage is high (48.65%).

As a whole, the above findings suggest that the models yield fairly accurate predictions of absolute poverty out-of-sample. Likewise, the rural model performs better than the urban model. Furthermore, the results indicate that calibrating the models to a higher poverty line (international line) improves their performances, while calibrating the models to a lower line (extreme line) does the opposite. Section 5.2 analyzes the cost-effectiveness and impacts of targeting.

5.2 Evaluating the cost-effectiveness and impacts of targeting the poor: Policy simulations

5.2.1 Population welfare under targeted policies

This section illustrates the pre- and post-transfer distributions of consumption expenditures for the redistribution schemes applied: universal coverage, uniform targeting, progressive targeting, and fair targeting of the poor. Figures 5 and 6 describe the distributions. Annex 4 shows a clearer view of the redistributions.

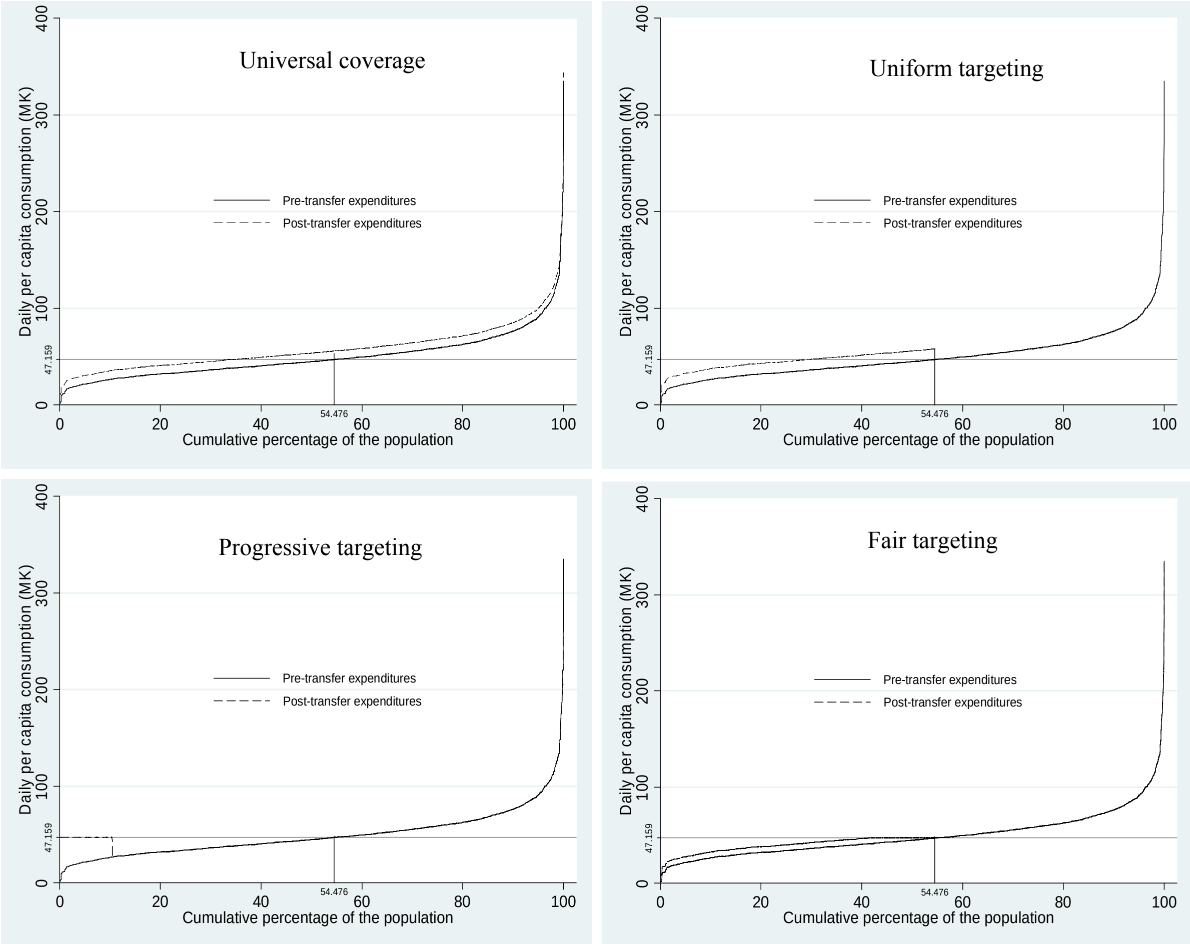

Figure 5: Pre- and post-transfer consumption expenditures under different transfer schemes (rural model).
Source: Own results based on Malawi IHS2 data.

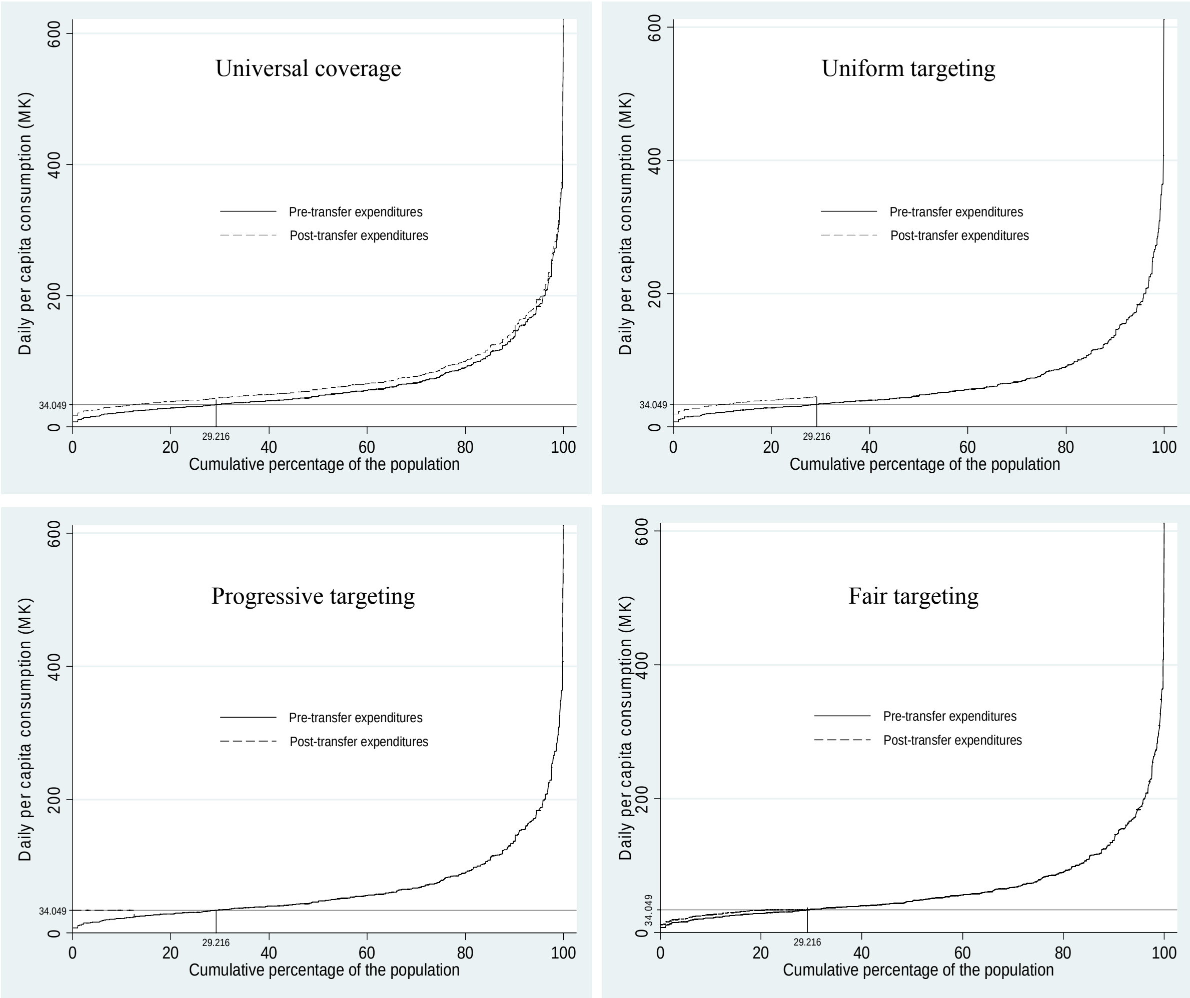

Figure 6: Pre- and post-transfer consumption expenditures under different transfer schemes (urban model). Source: Own results based on Malawi IHS2 data.

The panel to the upper left corner of Figure 5 shows that under a universal coverage, the available budget (net of costs) is distributed equally among individuals in the population, independently from their poverty status. Therefore, the entire curve of the pre-transfer expenditures shifts upward by a fixed amount (equal to the transfer amount), yielding the post-transfer curve. As a consequence, both pre- and post-transfer curves are parallel. The universal regime has the advantage of covering all of the poor. But, it creates two kinds of wastes: the first one is the excessive leakage to the non-poor who do not need transfers and the second one is the amount received by least poor (those just below the poverty line) in excess of their needs. Both kinds of wastes are indicated by the area delimited by the pre- and post-transfer curves above the poverty line. Under limited resources, reducing such wastes is of a paramount importance.

Under uniform targeting (upper right panel of Figure 5), only the poor receive cash transfers in a fixed amount. Therefore, only the portion of the curve below the poverty line moves upward by a fixed amount in the post-transfer distribution, whereas the section above the line remains unchanged after redistribution: the non-poor receive no transfers. This targeting scheme concentrates benefits on the poor and reduces excessive leakage to the non-poor; the average transfer per poor is higher compared to universal coverage. This is indicated by the margin between pre- and post-transfer curves. However, alike the universal regime, the uniform scheme provides transfers to some less poor in excess of their needs, and therefore changes the initial welfare ranking of the population.

With regard to progressive targeting scheme (lower left panel of Figure 5), transfers are distributed from bottom up: the poorest poor receives the amount just enough to bring him up to the poverty line, then the next poorest is served, and so on till the available budget (net of costs) is exhausted. Therefore, the lower section of the post-transfer curve matches exactly the poverty line, whereas the upper part remains identical to the pre-transfer distribution. The transition between both parts marks the exhaustion of the available budget. It is illustrated by the fall of the post-transfer expenditures down to the pre-transfer level. This targeting regime aims at reducing extreme poverty first. However, it is more costly than uniform targeting since it seeks the poorest out of the poor and grants them the exact transfer necessary to lift them out of poverty. Likewise, the poorest poor get richer than the less poor after transfer. As a result, the initial welfare ranking of the population changes. Therefore, a fair targeting scheme is applied.

The fair redistribution scheme respects the initial welfare ranking of the population as shown in the lower right panel of Figure 5. This scheme provides transfer amounts which ensure that: i) a poorer individual doesn't get richer than its less poor neighbor and ii) all of the poor lifted out of poverty after redistribution lie just at the poverty line, but not above. Therefore, only the portion of the pre-transfer curve below the poverty line shifts upward at a decreasing rate in the post-transfer curve and its upper part matches exactly the poverty line. This scheme aims at preserving the social hierarchy in the population. As concerns the urban model, the same trend applies (Figure 6).

All of the redistribution schemes have advantages, but also some limitations. Likewise, they are not exhaustive and the range of transfer options is broader, but they do provide some insights on the comparison of welfare gains from different policy choices.

5.2.2 Costs, benefits, and impacts of targeting

This section analyzes the cost-effectiveness and impacts of targeting. The magnitude of targeting costs, benefits, and impacts depends on program budget, model accuracy, the number of poor, and the poverty gap in the population. Table 5 presents the cost estimates of the redistribution schemes.

Table 5. Costs of targeting by model type and transfer scheme

Models \ Costs	Total transfer to the poor*	Costs of leakage to the non-poor	Administrative costs	Hidden costs	Total costs
Rural model					
Universal coverage (Zero targeting)	1645.02 (1395.58)	1374.69	532.89	0	3552.6
Uniform targeting (scheme 1)	1946.80 (2180.50)	486.74	1065.78	53.29	3552.6
Progressive targeting (scheme 2)	1912.52 (2142.12)	272.32	1243.41	124.34	3552.6
Fair targeting (scheme 3)	1696.74 (1900.43)	488.11	1243.41	124.34	3552.6
Urban model					
Universal coverage (Zero targeting)	88.22 (1035.62)	213.75	53.28	0	355.26
Uniform targeting (scheme 1)	80.14 (1660.96)	163.22	106.59	5.33	355.26
Progressive targeting (scheme 2)	162.86 (3375.47)	55.63	124.34	12.43	355.26
Fair targeting (scheme 3)	130.30 (2700.62)	88.19	124.34	12.43	355.26

Source: Own results based on Malawi IHS2 data. The cost estimates are given in million Malawi Kwacha (MK) using 2005 prices, US$1= MK118.42. The budget available for poverty reduction is set at US$30 million for the rural model and US$3 million for the urban model. *The average transfer per poor (in brackets) is given in MK.

Table 5 shows that the total transfer to the poor increases under the targeted program compared to universal coverage, with one exception. The urban poor receive in total a lower transfer under uniform targeting. This result is driven by the fact that the sum of leakage, administration, and hidden costs under uniform targeting is higher compared to universal coverage. As a consequence with a limited budget, the amount of funds to be redistributed to the poor, i.e. the total transfer to urban poor is lower under uniform targeting. The results may also be explained by the higher leakage of the urban model as shown in Table 4. Nonetheless, the average transfer per poor is higher under uniform targeting (MK1661) compared to universal coverage (MK1036) of urban poor. This indicates that even though all of the poor are covered and the total transfer is higher, the benefits of the program spread thin under universal redistribution. In addition, this scheme does not do much for the poorest. In fact, irrespective of the model, average transfer to the poor increases under the targeted programs. For example, the rural poor receive MK1396 on average under universal coverage against MK2181, MK2142, and MK1900 under uniform, progressive, and fair targeting, respectively. These results show that targeting does concentrate resources on the poor.

Furthermore, Table 5 indicates that the costs of leakage decrease substantially for both models, indicating sizable savings under the targeted programs. For instance, under the rural model, leakage costs decrease from about MK1.37 billion under universal coverage to MK486.7 million, MK272 million, MK488 million under uniform, progressive, and fair targeting, respectively. Conversely, administrative and hidden costs increase considerably under targeted schemes. For example, under the urban model administrative costs are estimated at MK53.28 million under universal coverage against MK106.59 million under uniform targeting, but this effect is weaker than the reduction in leakage costs.

Within targeted programs, none of the schemes consistently allocates the highest transfer to the poor. In rural areas, uniform targeting provides the highest transfer, whereas fair targeting grants the lowest transfer to the poor. Conversely, progressive targeting allocates the highest transfer, while uniform redistribution provides the lowest transfer to the poor in urban areas.

The above results broadly suggest that even though narrow targeting increases administrative and hidden costs, it concentrates resources on the poor and considerably reduces the costs of leakage to non-poor. Based the aforementioned results, we estimate in Table 6, the transfer efficiency and poverty impacts of targeting.

Table 6. Transfer efficiency and poverty impacts of targeting by model types

Models \ Indicators		Transfer efficiency			Post-transfer poverty (poverty impacts)		
		F	**F_1**	**F_2**	**P_o**	**P_1**	**P_2**
			Rural model				
Universal coverage		54.48	1.16	46.30	46.96 (-7.52)	0.11 (-0.04)	5.73 (-3.08)
Targeted program	scheme 1	80.0	0.83	54.80	41.58 (-12.90)	0.08 (-0.07)	4.45 (-4.36)
	scheme 2	87.54	0.86	53.83	44.05 (-10.42)	0.09 (-0.06)	3.79 (-5.02)
	scheme 3	77.66	1.09	47.76	41.49 (-12.99)	0.09 (-0.06)	4.34 (-4.48)
			Urban model				
Universal coverage		29.22	3.03	24.83	25.88 (-3.34)	0.06 (-0.02)	3.11 (-1.59)
Targeted program	scheme 1	32.93	3.43	22.56	21.42 (-7.80)	0.05 (-0.04)	2.41 (-2.29)
	scheme 2	74.54	1.18	45.84	16.68 (-12.53)	0.02 (-0.06)	0.59 (-4.11)
	scheme 3	59.64	1.73	36.68	20.97 (-8.27)	0.05 (-0.04)	2.35 (-2.36)

Source: Own results based on Malawi IHS2 data. Baseline poverty measures are estimated at P_o= 54.48%; P_1= 0.15; P_2= 8.81 under the rural model and P_o= 29.22%; P_1= 0.08; P_2= 4.70 for the urban model. Poverty impacts (in brackets) are measured as post minus pre-transfer poverty.

Considering the rural model, Table 6 suggests that transfer efficiency and post-transfer poverty improve under the targeted schemes compared to universal coverage. The transfer to the poor as a percentage of total transfer (F) and the transfer to the poor as a percentage of total program cost (F_2) increase, whereas the cost per unit of resources transferred (F_1) decrease under a targeted program. For instance under universal coverage, the program spends MK1.16 for every MK transferred to the poor, against MK0.83, MK0.86, and MK1.09

under a uniform, progressive, and fair targeting, respectively. Likewise, the transfer to the poor as a percentage of total program cost increases from 46.30% under universal coverage to 54.8%, 53.83%, and 47.76% under uniform, progressive, and fair targeting, respectively. Table 6 also indicates that under the rural model, the transfer efficiency differs considerably between targeted and untargeted regimes with exceptions. Under fair targeting, F_1 and F_2 do not improve much compared to universal coverage because of leakage costs.

Though progressive targeting provides the highest transfer (F) to the poor in rural areas, it yields the lowest poverty impact on P_o (i.e. the highest post-transfer poverty). Conversely, fair targeting with the lowest efficiency (F) achieves the highest poverty impact in terms of P_o. For instance, under fair targeting, the poverty incidence (P_o) is reduced by 13% against 10% under progressive targeting. However, under progressive targeting, the severity of poverty (P_2) is reduced by 5.02 versus 4.48 under fair targeting. These results are driven by differences between both schemes. Under progressive targeting, a higher total transfer lifts fewer poorer people out of poverty, whereas a lower total transfer lifts many less poor out of poverty under fair targeting. As concerns the poverty gap (P_1), there is no sizeable difference between the redistribution schemes applied in rural areas. These results suggest that none of the targeted schemes consistently yields the best transfer efficiency and post-transfer poverty in rural areas.

With regard to the urban model, F improves under a targeted program. Similarly, F_1 and F_2 improve considerably under progressive and fair targeting, but these estimates regress under uniform targeting compared to universal coverage. This result suggests that uniform targeting of urban poor does not improve transfer and cost-efficiency measures F_1 and F_2 compared to universal coverage, whereas progressive and fair targeting do. The result may be explained by the fact that uniform targeting transfers fewer resources to the poor in total due to higher costs compared to universal coverage. Nevertheless, the reduction in efficiency under uniform targeting is balanced by the far higher poverty impact and the higher average transfer that go to the poor (see Table 5). Unlike the rural model, progressive targeting consistently yields the best transfer efficiency and post-transfer poverty, followed by fair targeting.

As a whole, the above results suggest that the targeted schemes outperform a universal coverage of the population in Malawi. However, the finest redistribution doesn't consistently yield the best transfer efficiency, nor does it consistently improve post-transfer poverty. These results imply that the performances of a targeted program may depend on the welfare distribution of the population covered. Nonetheless, it is shown that better targeting improves resource efficiency and post-transfer poverty compared to universal coverage. What are the benefits from targeting? We answer this question by estimating the gains from targeting in Table 7.

Table 7. Benefits from targeting

Post-transfer poverty \ **Costs and benefits**		**Total costs**		**Direct benefits**
		Targeted program	**Universal coverage**	
Rural model				
Poverty level	Po = **41.58** (scheme 1)	3552.6	5550.73	1998.13 (6.8%)
	Po ≈ **44.05** (scheme 2)	3552.6	4389.09	836.49 (2.3%)
	Po = **41.49** (scheme 3)	3552.6	5601.60	2049.29 (6.9%)
Urban model				
Poverty level	Po = **21.42** (scheme 1)	355.26	569.78	214.52 (2.8%)
	Po ≈ **16.68** (scheme 2)	355.26	855.73	500.47 (11.5%)
	Po = **21.00** (scheme 3)	355.26	571.90	216.64 (2.8%)

Source: Own results based on Malawi IHS2 data. Direct benefits are measured as the amount by which an untargeted program would have to be increased in order to achieve the targeted poverty level P_0. The budget available for poverty reduction is set at US\$30 million for the rural model and US\$3 million for the urban model. The figures in brackets indicate the additional reduction of poverty achievable with the direct benefits. Cost estimates are given in million Malawi Kwacha (MK) using 2005 prices. US\$1= MK118.42.

Table 7 suggests that targeting Malawi's poor is potentially beneficial; with a targeted program, fewer resources can achieve the same post-transfer poverty as a universal coverage of the population. Furthermore, Table 7 indicates that the higher the impact on poverty (i.e. the lower the post-transfer poverty), the higher the benefits from targeting. In other words, the scheme that reduces poverty incidence the most yields the highest targeting benefits. For example, to achieve a post-transfer poverty of about 44% (scheme 2) in rural areas, a universal coverage would cost about MK4.40 billion, whereas a targeted program (progressive targeting) would cost only MK3.553 billion. Thus, the benefits from targeting are estimated at MK836.49 million. On the other hand, achieving a lower post-transfer poverty (i.e. higher poverty reduction) of 41.58% under uniform targeting would result in total benefits of MK1.998 billion compared to universal coverage. Further simulations show that the benefits derived from uniform targeting (scheme 1) would further reduce the poverty incidence by 6.8%, whereas the benefits from progressive and fair targeting (schemes 2 and 3) would reduce the poverty incidence by 2.3% and 6.9%, respectively if these benefits were uniformly targeted at the poor. As concerns the urban model, the same trend applies. However, the benefits from targeting are much lower compared to the rural model. This may be explained by the lower budget and lower number of urban poor.

It appears from the overall results that using proxy indicators to reach the poor is more target-, cost-, and impact-effective than universal provision of benefits in Malawi.

5.3 Efficiency of targeted agricultural support programs versus the new system

Table 8 compares the targeting efficiency of the new system (rural model) to the performances of Starter Pack and AISP programs, both of which were administered through a community-based targeting system.

Table 8. Targeting efficiency of Starter Pack, AISP, and new system

Program type	**Poverty accuracy** (%)	**Undercoverage** (%)	**Leakage** (%)
2000/2001 Starter Pack[1]	65.02	34.98	61.81
2006/2007 AISP[2]	54.00	46.00	54.00
New system (rural model)	71.48	28.52	26.65

Source: Own results based on Malawi IHS2 data. [1]Main cropping season and rural areas estimates. [2]Estimates based on Dorward et *al.* (2008).

Table 8 indicates that under the new system, about 71% of the poor would be correctly targeted and would receive agricultural inputs, while only 65% and 54% of the poor received benefits under the Starter Pack and AISP programs, respectively. As a result, the undercoverage of the new proxy system is lower compared to the targeted programs. More importantly, Table 8 suggests that the Starter Pack and AISP programs leaked substantial quantities of fertilizer and seeds to non-poor households as their leakages rates amount to 62% and 54%, respectively, against 27% under the new proxy system. This result implies that under the new system, a program's leakage can be cut down by two-thirds. In conclusion, the new system is more target-efficient than the Starter Pack and AISP programs. Is the system also more cost-efficient than these programs? Table 9 estimates the cost-effectiveness of the programs under the new proxy system and community-based targeting.

Table 9. Costs and transfer efficiency of Starter Pack and AISP versus new system

Costs / Programs	Total transfer to the poor[3]	Costs of leakage	Administra-tive costs	Hidden costs	Total costs	F	F_1	F_2
2000/2001 Starter Pack	562.61 (772.11)	534.84	195.39	9.77	1302.62[1]	51.27	1.32	43.19
Starter Pack under new system	649.97 (811.33)	242.33	390.79	19.54	1302.62	72.84	1.00	49.90
2006/2007AISP	2777.51 (4397.33)	2940.89	1018.11	50.91	6787.41[2]	48.57	1.44	40.92
AISP under new system	3386.71 (3825.58)	1262.67	2036.22	101.81	6787.41	72.84	1.00	49.90

Source: Own results based on Malawi IHS2 data. The cost estimates are given in million Malawi Kwacha (MK). [1]The cost of the targeted Starter Pack is estimated at US$11 million based on Smith (2001). [2]The results are based on the net cost of the main component (Urea and NPK) of the AISP program and are estimated at US$57million. [3]The average transfer per household (in brackets) is given in MK.

Table 9 shows that the Starter Pack program (under community-based targeting) transferred an average amount of MK772 (input equivalent) to the poor against MK811 under the new system. Likewise, the costs of are cut down by 55% compared to Starter Pack; from MK535 million to MK242 million. Estimates of the transfer efficiency measures also suggest that administering the Starter Pack program with the new system would have been more efficient, transferring 72% of total transfer to the poor (i.e. 50% of program costs) compared to 51% (i.e. 43% of program costs) under community-based targeting. Likewise, under the new system, MK1 is spent for every MK transferred to the poor against MK1.32 under community-based targeting of Starter Pack. The same trend applies to the AISP program with one exception. Under the new system, the average transfer per poor decreases though the total transfer to the poor increases: more poor have been covered by the program and increases in total transfer (in percentage terms) to the poor are less than increases in program's coverage.

These results show that the new proxy indicator system can potentially improve the cost and transfer efficiency of targeting compared to the currently used mechanisms for identifying the rural poor and smallholder farmers in Malawi.

6. Conclusions and Policy Implications

This paper estimates the cost-effectiveness and impacts of targeting by proxy indicators in Malawi. Two proxy means test models are developed for rural and urban Malawi based on quantile regression. The costs, benefits, and impacts of targeting under the proxy system are compared to the performances of universal interventions and the community-based targeting system.

There is compelling evidence in favor of targeting since considering all costs does not make a targeted program cost- and impact-ineffective. Findings suggest that the new system is fairly accurate and more target-efficient than the currently used mechanisms for targeting agricultural inputs in the country. Likewise, simulation results indicate that targeting the poor and smallholder farmers is more cost- and impact-effective than universal coverage of the population. Though administrative costs increase with finer targeting, the results indicate that the overall benefits outweigh the costs of targeting. Targeting concentrates resources on the poor and produces the highest impact on poverty. Furthermore, the newly designed system appears to be more cost-efficient than the 2000/2001 Starter Pack program and the 2006/2007 Agricultural Input Support Program (AISP). Thus, under the new system it is possible to reduce leakage and undercoverage rates considerably and improve thus the cost and transfer efficiency of development programs in the country.

The performances of the new system can be further improved in various ways. Administrative costs can be cut by sharing the same system between several programs. Likewise, the costs of leakage can be reduced by recouping through taxation. The proxy system can also be combined with other targeting methods. For example, the system can be combined with geographical targeting to target regions with disproportionate numbers of poor and then target poor households within these regions. The estimation of separate models for urban and rural households in this research illustrates such a combination. Proper implementation and management can also help reduce targeting errors and program costs. If well implemented, the proxy system developed has the potential of reducing the displacement of agricultural subsidies in the country. Finally, the research could be applied in other developing countries with similar targeting problems.

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Annexes

Annex 1. Malawi's poverty rates by region and poverty line (status as of 2005)[39]

Type of poverty lines	Poverty lines (MK*)	Poverty rate (in percent of people)			Poverty rate (in percent of households)		
		national	rural	urban	national	rural	urban
Extreme	29.81	26.21	28.66	8.72	19.94	22.08	5.95
National	44.29	52.40	56.19	25.23	43.58	47.13	19.67
International	59.18 (US$1.25 PPP)	69.52	73.59	40.26	61.04	65.20	33.08

Source: Own results based on Malawi IHS2 data, Chen and Ravallion (2008), and the World Bank (2008). *MK denotes Malawi Kwacha, national currency. PPP stands for Purchasing Power Parity.

Annex 2. Results of Quantile regression calibrated to the national poverty line (rural model)

	Indicator set	Parameter estimates	Standard errors	T-values
Wald statistic = 3377.251* Point of estimation: 56.408**		**Likelihood ratio: 3082.501*** Number of observations= 6560**		
	Intercept	4.337***	0.045	96.88
Control variables	Agricultural development district is Mzuzu	-0.015	0.048	-0.32
	Agricultural development district is Kasungu	0.184***	0.042	4.38
	Agricultural development district is Salima	-0.028	0.048	-0.59
	Agricultural development district is Lilongwe	0.090**	0.044	2.07
	Agricultural development district is Machinga	-0.237***	0.043	-5.53
	Agricultural development district is Blantyre	-0.156***	0.043	-3.66
	Agricultural development district is Ngabu	-0.154***	0.055	-2.80
Best 10 indicators	1. Household size	-0.154***	0.004	-43.25
	2. Wireless radio ownership	0.109***	0.014	7.60
	3. Floor of main dwelling is predominantly made of smoothed cement	0.360***	0.022	16.16
	4. Bicycle ownership	0.148***	0.016	9.32
	5. Lighting fuel is electricity	0.631***	0.065	9.69
	6. Panga ownership	0.084***	0.015	5.75
	7. Highest educational qualification acquired in household is Junior Certificate of Education (JCE)	0.120***	0.028	4.31
	8. Does any household member sleep under a bed net?	0.121***	0.015	8.32
	9. Rubbish disposal facility is public rubbish heap	-0.082***	0.019	-4.32
	10. Household head can read in Chichewa language	0.117***	0.015	7.87

Source: Own results based on Malawi IHS2 data. **** denotes significant at the 99% level. ** denotes significant at the 95% level.*

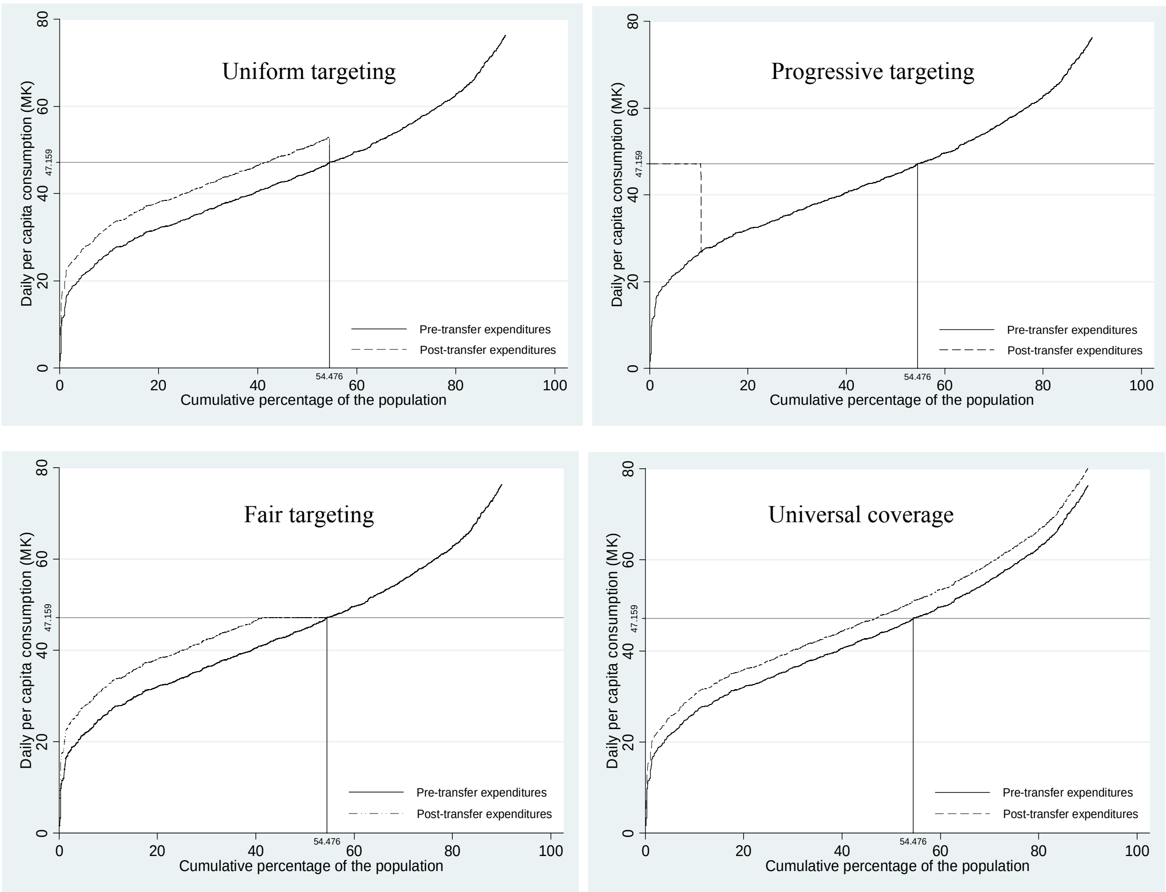
[39] These rates differ slightly from the official statistics because of errors in the weights of the IHS2 report.

Annex 3. Results of Quantile regression calibrated to the national poverty line (urban model)

Wald statistic = 880.603***		**Likelihood ratio: 1017.934*****		
Point of estimation: 24.685		**Number of observations= 960**		
	Indicator set	**Parameter estimates**	**Standard errors**	**T-values**
Control variables	Intercept	4.467***	0.112	40.04
	Lilongwe city	-0.052	0.066	-0.79
	Zomba city	-0.324***	0.080	-4.05
	Blantyre city	-0.187***	0.065	-2.89
Best 10 indicators	1. Household size	-0.220**	0.015	-14.52
	2. Household has no toilet facility	-0.289**	0.113	-2.56
	3. Household has a cellular phone in working condition	0.625***	0.064	9.81
	4. Number of separate rooms occupied by household excluding toilet, storeroom, or garage	0.124***	0.022	5.74
	5. Household head can read in Chichewa language	-0.134**	0.065	2.06
	6. Sewing machine ownership	0.243***	0.093	2.62
	7. Highest class level ever attended by members is superior or post-secondary	0.492***	0.098	5.03
	8. Main source of cooking fuel is collected firewood	-0.317***	0.058	-5.50
	9. Lighting fuel is electricity	0.366***	0.060	6.12
	10. Floor of main dwelling is predominantly made of smoothed cement	0.181***	0.050	3.65

Source: Own results based on Malawi IHS2 data. **** denotes significant at the 99% level.*
*** denotes significant at the 95% level.*

Annex 4: Pre- and post-transfer consumption expenditures under different transfer schemes (rural model).



Source: Own results based on Malawi IHS2 data. For a better viewing, the upper 10% of the distribution is not shown in the graph.

CHAPTER V

GENERAL CONCLUSIONS

5.1 Comparative Analysis of Model Results

We analyze in this section the overall results of the models. Table 8 compares the performances of different regression methods used to develop proxy means test models for rural Malawi.

Table 8. Rural model's results under different estimation methods

Targeting ratios Poverty Line	Method	Cut-off values (MK)	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
National	***WLS***	3.85	**72.00** (69.7; 74.2)	**28.00** (25.8; 30.3)	**26.32** (23.4; 29.1)	**-0.79** (-2.4; 1.0)	**70.32** (64.9; 73.5)
	WL	0.48	**71.61** (69.6; 74.0)	**28.39** (26.0; 30.4)	**27.10** (25.3; 30.82)	**-0.61** (-3.5; 0.2	**70.32** (59.7; 69.6)
	WL categorical	37	**68.52** (66.1; 70.6))	**31.48** (29.4; 33.9)	**28.00** (69.6; 74.0)	**-1.64** (69.6; 74.0)	**65.03** (69.6; 74.0)
	W Quantile	3.90	**71.48** (69.3; 73.6)	**28.52** (26.4; 30.7)	**26.65** (23.7; 29.6)	**-0.88** (-0.0; 0.8)	**69.61** (64.5; 72.9)
International	***WLS***	4.03	**82.33** (80.9; 83.9)	**17.67** (16.1; 19.1)	**16.60** (14.7; 18.4)	**-0.70** (-2.3; 1.0)	**81.27** (77.7; 83.3)
	WL	0.56	**82.61** (81.1; 84.2)	**17.39** (15.8; 18.9)	**16.18** (14.4; 18.1)	**-0.79** (-2.2; 0.9)	**81.40** (77.9; 83.6)
	WL categorical	40	**84.52** (78.8; 82.9)	**15.48** (14.0; 17.1)	**18.87** (17.0; 21.1)	**2.23** (0.6; 3.8)	**81.13** (78.9; 83.0)
	W Quantile	4.30	**80.38** (78.8; 82.1)	**19.62** (17.9; 21.2)	**16.92** (15.0; 18.8)	**-1.77** (-3.3; -0.1)	**77.69** (74.2; 81.4)
Extreme	***WLS***	3.56	**49.93** (46.4; 53.4)	**50.07** (46.6; 53.6)	**39.21** (34.2; 44.4)	**-2.44** (-3.9; -1.0)	**39.08** (30.9; 48.1)
	WL	0.36	**53.05** (49.6; 56.7)	**46.95** (43.3; 50.4)	**38.54** (33.5; 44.1)	**-1.89** (-3.4; -0.4)	**44.64** (35.9; 53.7)
	WL categorical	18	**46.13** (42.3; 49.8)	**53.87** (50.2; 57.7)	**38.13** (33.3; 44.0)	**-3.54** (-5.0; -1.9)	**30.39** (21.9; 39.6)
	W Quantile	3.30	**48.71** (45.2; 52.4)	**51.29** (47.6; 54.8)	**40.57** (35.4; 46.1)	**-2.41** (-4.0; -0.9)	**37.99** (29.6; 47.2)

Source: Own computations based on Malawi IHS2 data. Bootstrapped prediction intervals in brackets. Cut-off values are expressed in Logarithm Malawi Kwacha (MK) under the WLS and probability for the WL method.

Table 8 indicates that when calibrated to the national poverty line, the estimation methods achieve similar levels of targeting performances with minor exceptions. The categorical indicators model (WL categorical) achieves the lowest performances. For example, the latter yields a poverty accuracy of about 69% against an average of 72% under the other methods. This result is explained by the model's transformation after estimation. Indeed, the untransformed model's performances are comparable to the other methods. For example, its poverty accuracy and BPAC are estimated at 72.19% and 70.13% points, respectively (see annex 3, page 101).

The same trend emerges when the model is calibrated to the international and extreme poverty lines. Furthermore, irrespective of the estimation method, the performances of the model improve with the calibration to the international poverty line. For example, the poverty accuracy is set at just over 80%, whereas the estimated leakage is lower than 20%. The BPAC ratio also improves considerably; it is estimated at about 80% points. However, the estimated performances drop considerably with the extreme poverty line which is lower. The results of the urban model follow the same pattern (appendix 10).

Therefore, we conclude from the above results that there are no sizable differences in terms of targeting performances between the estimation methods. Apart its key features, such as simplicity and easy use, the categorical indicators model does not enjoy any major advantage compared to the other methods. Though the number of indicators was limited to ten, such a categorical model embeds much more information than any estimated model. Nonetheless, categorical indicators are less prone to measurement errors and easier to use than continuous variables. Hence, when the risk of measurement errors is high so that it may render the system ineffective, we strongly suggest using a categorical indicators model for targeting the poor.

5.2 Summary and Conclusions

This research analyzes the targeting the poor and smallholder farmers. The study explores potential models that might improve the targeting efficiency of development policies and assesses the cost-effectiveness and poverty impact of targeting in Malawi. The general problematic of targeting the poor is discussed with special emphasis on Malawi. The basic rationale behind targeting is to maximize the coverage of the poor with limited fiscal and donor resources. Focusing resources on those who need them the most is likely to result in higher marginal impact and foster economic growth. Moreover, historically public spending tends to exclude the lower strata of the population. Therefore, without active efforts to target resources at the poor, even the so-called “universalist programs” will miss the poor (Grosh, 2009).

In Malawi, there exist a large number of development and safety net programs, most of which are uncoordinated short-term relief or emergency responses (Smith, 2001). Most of these programs are administered through community-based targeting in which local authorities select program beneficiaries based on their assessment of the household living conditions. However, they have been characterized by poor targeting: they cover a limited number of poor and smallholder farmers and leak program benefits to a significant number of non-poor. For example, the Starter Pack of 2000/2001 failed to reach 35% of rural poor and wrongly targeted 62% of non-poor. Furthermore, a recent evaluation of the Agricultural Input Support Program (AISP) of 2006/2007 suggests that 46% of the poor received no fertilizer subsidy, whereas 54% of non-poor were wrongly targeted by the program (Dorward et *al.*, 2008). On top of this, the report emphasizes that subsidized fertilizer received by these households appeared to have displaced a large proportion of commercial purchases typically made by these households in the absence of subsidy. Almost all interventions have targeting problems in the country (GoM and World Bank, 2007). In the period 2003-2006, including emergency aid and disaster response, the combined safety nets/social protection system amounted to an average of more than US$134 million per year; that is about 6.5% of the country's GDP. Therefore, there are compelling reasons to ensure that targeted programs effectively reach the poor (World Bank, 2007).

Low targeting efficiency combines with poor implementation can seriously impede progress toward achieving the Millennium Development Goals (MDGs), long-term food security and sustainable poverty reduction in the country. The level of funding for different programs is not necessarily inadequate, but many programs do suffer from limited beneficiary coverage, mis-targeting and significant leakages (World Bank, 2007). To reverse this trend and ensure that development policies reach their intended beneficiaries, more accurate and operational targeting methods need to be devised for policy makers and development practitioners in the country. One such method is targeting by proxy means tests. These tests seek a few indicators that are less costly to identify, but are sufficiently correlated with household income to be used for poverty alleviation (Besley and Kanbur, 1993).

Compared to the currently used targeting methods in the country, proxy means tests have the merit of making replicable judgments using consistent and visible criteria (Coady et *al.*, 2002). They are fairly accurate and less prone to criticism of politicization or randomness. They are also less costly than verified means tests and appropriate for large and long term programs. The use of proxy means tests extends well beyond targeting and their efficacy is demonstrated in various studies (Coady et *al.*, 2009; Johannsen, 2009; Narayam and Yoshida, 2005; Schreiner, 2006; Benson et *al.*, 2006; Zeller et *al.*, 2006; Zeller et *al.*, 2005a, b; Zeller and Alcaraz V., 2005a, b; Coady et *al.*, 2004; Ahmed and Bouis, 2002; Baulch, 2002; Braithwaite et *al.*, 1999; Grosh and Baker, 1995; Grosh, 1994; Glewwe and Kanaan, 1989). Though the results from previous researches exhibit some targeting errors, a systematic comparison of these studies is hampered by a number of factors, including differences in the number and type of variables, their practicality, the poverty rate, the estimation method, and whether the models are validated out-of-sample or not.

Targeting the poor presupposes first the definition of a target group, i.e. the poor and second, the establishment of mechanisms or methods to reach this target group in the population. Therefore, in the introductory chapter, we define poverty first and establish its profile in Malawi. We then review available targeting methods, including their advantages and limitations. In this respect, we emphasize the use of proxy means tests and survey the main targeted programs in Malawi. Poverty is defined today as a state of long-term deprivation of well-being considered adequate for a decent life (Aho et *al.*, 2003). It is synonymous of a deficit in consumption and expenditures and does not refer to people in temporary needs. This definition is standard although narrow view of poverty (Benson, 2002). Nevertheless, the concept of monetary poverty is adopted by the GoM and the MDGs.

This research draws on the Malawi Second Integrated Household (IHS2) survey data of 2004/2005. The IHS2 is a nationally representative survey which covered 11,280 households and a wide range of household socioeconomic indicators (NSO, 2005b). In total, about 800 variables were prepared from the IHS2 dataset. The criteria for the selection of indicators were based on Zeller et *al.* (2006) and included practicability criteria regarding the ease and accuracy with which information on the indicators can be quickly elicited in an interview as well as considerations regarding the objectiveness and verifiability of an indicator. Likewise, the number of indicators was limited to the best ten in order to allow for an operational use of the models and keep the costs of data collection low.

Using a variety of estimation methods, such as Weighted Least Square, Weighted Logit, and Quantile regressions along with stepwise selection of variables, we propose empirical models for improving the poverty outreach of agricultural and development policies in rural and urban Malawi. Furthermore, the research analyzes the out-of-sample performances of different estimation methods in identifying the poor and smallholder farmers. Out-of-sample tests gauge the robustness or predictive power of the models. They ascertain how well the models will likely perform when used to identify the poor and smallholder farmers on the field. As such, they can be regarded as good substitutes for direct field-tests.

To conduct the validation tests, the initial samples were first split into two sub-samples - a calibration and a validation samples – following the ratio 67/33 and the same stratification as the original sample. This design mimics the initial sample selection process and ensures that all strata are adequately represented in the model calibrations. With the 67:33 split, we put more emphasis on the model calibrations than validations. Splitting the initial sample implies a loss in degree of freedom. Instead, one can estimate the models based on the full set of observations and validate those using bootstrapped samples of the total sample. However, by using a third of the sample not used in the model calibrations, we envisioned the worst case scenario for the predictions.

In addition, the model robustness was assessed by estimating the prediction intervals using bootstrapped simulation methods. Bootstrap is the statistical procedure which models sampling from a population by the process of resampling from the sample (Hall, 1994). Unlike standard confidence interval estimation, bootstrap does not make any distributional assumption about the population and hence does not require the assumption of normality. The developed models were calibrated to three different poverty lines - the national, international, and extreme lines - as a set of policies or different development institutions might explicitly target different poverty groups in the population.

It is often argued that targeting is cost-ineffective and once all targeting costs have been considered, a finely targeted program may not be any more cost-efficient and may not have any more impact on poverty than a universal program. We assessed whether this is the case using the models developed for Malawi. Based on the principles of targeting, we estimated the cost-effectiveness and impacts of targeting the poor. Three targeted schemes were considered. The first one is a *uniform targeting* or equal distribution of benefits to the poor, the second scheme consists of a *progressive targeting* or distribution of benefits to the poor starting from the bottom welfare spectrum, whereas the third scheme or *fair targeting* distributes transfers to the poor while respecting the initial welfare ranking of the population. These schemes were compared to a *universal distribution* of benefits or complete coverage of the population (untargeted program).

In order to fit with the existing institutional capacity necessary for handling a targeted program, we assumed a realistic transfer scheme to cover 20% of the population and set the total annual budget available for targeting at US$33 million (US$30 million for the rural population and US$3 million for the urban population). This amount is approximately equivalent to the total costs of the SPI and represents just about 1% of Malawi's GDP in 2005[40]. With respect to administrative and hidden costs of targeting, they were set following Smith and Subbarao (2003), Smith (2001), and Besley and Kanbur (1993) who hypothesize that the finer the targeting, the higher the costs. Furthermore, we assessed whether the newly developed system is more efficient both in terms of targeting performances and costs than the targeted Starter Pack program of 2000/2001 and the Agricultural Input Subsidy Program (AISP) of 2006/2007, both of which were administered through community-based targeting mechanisms.

The main results of the study are presented in three chapters organized in research articles. Estimation results provide pertinent conclusions about the potential contributions of targeting by proxy means tests in Malawi. Under the new system, mis-targeting is considerably reduced and the targeting of development policies improves compared to the currently used mechanisms in the country. Findings suggest that all of the estimation methods achieve approximately the same level of targeting performances out-of-sample. The rural

[40] Malawi's GDP was estimated at US$2.9 billion in 2005 (World Bank, 2008).

model achieves an average poverty accuracy of about 72% and a leakage of 27% when calibrated to the national poverty line of MK44.29. On the other hand, the urban model yields on average a poverty accuracy of about 62% and a leakage of 39% when calibrated to the same poverty line. These results suggest that any of the estimation methods is appropriate for developing proxy means test models, as far as targeting performances are concerned. They also indicate that the estimation methods cannot be discriminated based on targeting performances alone. Other factors, such as algorithm complexity and knowledge requirements, etc. should be considered in choosing the best method for developing a proxy means test model. Nonetheless, when the risk of measurement errors is high, the categorical indicators model is more appropriate for targeting the poor.

The results are also confirmed by the Receiver Operating Characteristic (ROC) curves of the models which show that there is no sizable difference in aggregate predictive accuracy between the methods. The ROC curve is a powerful tool that can be used by policy makers and project managers to decide on the number of poor a program or development policy should reach and ponder on the number of non-poor that would also be wrongly targeted. Likewise, the results show that calibrating the models to a higher poverty line improves their targeting performances, while calibrating the models to a lower line does the opposite. For example, under the international poverty line of US$1.25 (i.e. MK59.18 PPP), the rural model covers about 82% of the poor and wrongly targets only 16% of non-poor, whereas the urban model covers about 74% of the poor and wrongly identifies 26% of non-poor. On the other hand, using an extreme poverty line of MK29.81 disappointingly reduces the model poverty accuracy and leakage: the rural model yields a poverty accuracy of 51% and a leakage of 39% while the urban model yields a poverty accuracy of about 48% and a leakage of 68%. These findings are relevant for decision makers and program managers, national and international institutions as they consider which categories of poor to target in the population.

In all of the estimations and under the same poverty line, the rural model performs better than the urban model. This result is partly driven by the low level of poverty rate in urban areas. Estimates of the variance show that the result may be explained by the greater variability in the welfare indicator for urban households and between different urban centers in the country. Nevertheless, even though undercoverage and leakage are high in urban areas, these errors amount to a relatively small number of households; less than 15% of Malawians live in urban areas. Likewise, estimates of the prediction intervals suggest that the urban model is less robust than the rural model. This is due to the lower size of the sample used to validate the urban model.

Furthermore, irrespective of the estimation method and poverty line applied, the models yield some targeting errors, though the errors decrease with increasing poverty line. These errors can be attributed to the estimation method idiosyncratic error or probable measurement errors in the dependent variable and model covariates. Nonetheless, a breakdown of targeting errors by poverty deciles indicates that the models perform well in terms of those who are mistargeted; covering most of the poorest deciles and excluding most of the richest ones. These results have obvious desirable welfare implications for the poor and smallholder farmers. They suggest that targeting using the newly developed system will be progressive, concentrating benefits on the poorest and leaking few resources to the least poor.

The presence of targeting errors does however, point to a fundamental issue: proxy means tests can improve the poverty outreach of a development policy, but like any other targeting method, they are not a perfect device for identifying the poor. The level of these errors will affect the decision as whether to target or not, how to target, and which method to use for targeting. It is all important to emphasize that a core objective of this research is to predict, but not to infer a causal relationship on poverty. Therefore, the models selected can only predict poverty, but cannot explain it.

There is compelling evidence in favor of targeting under the redistribution schemes applied. Simulation results suggest that targeting Malawi's poor and smallholder farmers is more cost- and impact-effective compared to universal coverage. Better targeting not only reduces the Malawian Government's direct costs for providing benefits, but also reduces the total cost of a targeted program. With a targeted transfer program, fewer resources achieve the same post-transfer poverty as a universal coverage of the population. Finer targeting concentrates resources on the poor, whereas under universal coverage, benefits spread thin. With respect to the rural model, the transfer to the poor as a percentage of total transfer increases from 54.48% under universal coverage to 87.54% under progressive targeting.

Though administrative costs increase with finer targeting, the results indicate that the overall benefits outweigh the costs of targeting. Incorporating administrative and hidden costs does not make finer targeting cost-ineffective. Likewise, finer targeting reduces the costs of leakage by a sizable margin and produces the highest impacts on poverty compared to universal regimes. Considering the rural model, the leakage of the program is cut down by about 80% under progressive targeting and 65% under uniform and fair targeting. Likewise, simulation results suggest that a fair redistribution scheme reduces rural poverty incidence by 13% against 8% under universal coverage.

However, the finest redistribution doesn't consistently yield the best transfer efficiency, nor does it consistently improve post-transfer poverty. While none of the targeted schemes consistently yields the best transfer efficiency and post-transfer poverty in rural areas, progressive targeting appears to be the best scheme in urban areas. These findings imply that the transfer efficiency of a targeted program may depend on the welfare distribution of the population covered. Nonetheless, the redistribution schemes applied are not exhaustive and the range of transfer options is broader, but they do provide some insights on the comparison of welfare gains from different policy choices.

More importantly, the newly designed system appears to be more target- and cost-efficient than the 2000/2001 Starter Pack and the 2006/2007 Agricultural Input Support Program (AISP). While the Starter Pack and the AISP transferred about 50% of total transfer, under the new system about 73% of transfer are delivered to the poor and smallholder farmers. Likewise, under the new proxy system the costs of leakage are cut down by 55% and 57% for the Starter Pack and AISP, respectively. Thus, with the new system it is possible to reduce leakage and undercoverage rates and improve the cost and transfer efficiency of development programs in the country.

In general, the sets of proxy indicators selected capture the multidimensionality of poverty. Likewise, they reflect the local communities' understandings of the phenomenon. They broadly include the poverty indicators perceived by Malawian households as important correlates of their welfare (see for example Benson et *al.*, 2006). They consist of variables related to dimensions, such as household demography, education, housing, and asset ownership. These indicators are objective and most can be easily verified. They do not include any monetary or subjective variables. While subjective indicators can be powerful poverty indicators, they can hardly be verified. Thus, such indicators allow strategic answers by the respondent depending on his or her expectations from the interview. Likewise, with the lack of market transactions, estimations of monetary values (e.g. assets) often result in imprecise measurements.

All of the coefficients on the parameters exhibit signs which are consistent with expectations and economic theory. Information on the best indicators can be collected with a fairly high degree of accuracy. However, the collection of such information might entail an effective verification process to reduce bribery, misreports and fraudulent information from the enumerators as well as potential beneficiaries who may intentionally provide false information to qualify for program benefits. In this respect, one could also set up a supervisory system with incentives, such as bonus and malus for the enumerators. The system should facilitate the verification of the information provided by the beneficiary through e.g. random home-visits, triangulation, etc. Likewise, households can be interviewed using random models in order to mitigate the effects of strategic behaviors. This process implies that potential beneficiaries do not know in advance which indicators will be used to evaluate whether they qualify for program benefits or not. A pool of models with different combinations of indicators can be developed for that purpose.

There are various ways on how to reduce the observed targeting errors and costs and further improve the efficiency of targeting by the proxy means test system. Administrative costs could be cut by sharing the same system between several programs or by combining different targeting methods. As mentioned earlier, in Malawi there exist a large number of development programs targeted at the poor and vulnerable households. Sharing the system between those programs would considerably cut down the costs of targeting and would further improve the targeting efficiency of the system if a better coordination is established between programs. Likewise, as others have mentioned, the costs of leakage can be reduced by recouping through taxation of the non-poor if feasible.

If new estimation methods that improve the indicator correlation with poverty are found, undercoverage and leakage rates can also be reduced. To this end, currently existing options, such as two-step methods (see for example Grootaert et *al.*, 1998; Zeller et *al.*, 2005) and poverty minimization algorithms (see for example Ravallion and Chao, 1989; Glewwe, 1992) are more complex compared to the methods applied in this research. Ultimately, they compromise the practicality of proxy means testing.

Furthermore, proper implementation mechanisms and management options can help reduce targeting errors and program costs. Indeed, implementation is an important determinant of targeting performance (Coady et *al.*, 2004). Local awareness through the media can improve the coverage of the poor. As underlined by Coady et *al.* (2002), no matter how well or badly the statistical formula works, if the poor don't register for the program, it will have high undercoverage. Likewise, costs can be reduced by ensuring that potential beneficiaries have easy access to offices, are well informed about the program and the rules and documentation required. Qualification to the program can also be made conditional upon the participation to other targeted programs, such as nutrition, education, public works, etc. Stigma is a powerful means for reducing leakage to non-poor, but it can also discourage participation among the poor and work against the promotion of dignity and self-worth as an outcome of development (Coady et *al.*, 2002).

Valid proxy indicators are difficult to establish. The fact that we stress the use of proxy means tests in this research does not imply that other potential targeting methods should be disregarded. Indeed, targeting methods are not mutually exclusive and may work better in combination as long as this is feasible (Coady et *al.*, 2002). Therefore, the system developed can be combined with other methods in a multi-stage targeting process. For example, geographical targeting can be used to select regions with disproportionate number of poor within Malawi and then the proxy means system can be used to screen households within the selected regions. In this context, it is worth mentioning that the fact that we estimate separate models for rural and urban areas of Malawi, combined with differences in poverty rates between both areas implies to some extent a combination of geographical and proxy means targeting. Similarly, after selecting program beneficiaries with the proxy indicators, the results can be discussed with community members to integrate their assessment of who deserves benefits and who does not. Region-specific models can also be devised.

The models developed offer a better alternative for targeting the poor and smallholder farmers in Malawi. They can be used in a wide range of applications, such as:

- *identifying and targeting poor and smallholder farmers;*

- *improving the existing targeting mechanisms of agricultural input subsidies which rely on community-based targeting systems;*
- *assessing household eligibility to welfare programs and safety net benefits;*
- *producing estimates of poverty rates and monitoring changes in poverty over time as the country and donors cannot afford the costs of frequent and comprehensive household consumption expenditure surveys;*
- *estimating the impacts of development policies targeted to those living below the poverty line and;*
- *assessing the poverty outreach of microfinance institutions operating in the country.*

This broad range of applications makes the models potential policy tools for the country's decision makers and program managers.

5.3 Some Policy Implications and Outlook

There is a long standing belief that better targeting of public policy can play a major role in alleviating poverty. However, better targeting is not a panacea that would end poverty, but a means to reach the poor and smallholder farmers. Given the widespread and deep poverty in Malawi, targeted development policies, such as input subsidies, food-for-work, public work programs, etc. need to be well designed and sustained for a substantial amount of time in order to have a meaningful impact on the country's poor population. Malawi can achieve a lot with the current level of funding if programs are better targeted and rationalized (World Bank, 2007). The newly developed system, if well implemented can help accomplish such a goal.

In any targeted interventions, there are operational challenges. Lessons from previous experiences can greatly help policy makers and development practitioners improve the targeting and implementation of ongoing and future programs in the country. Likewise, these programs should be flexible enough to accommodate further improvements. Similarly, the system can be designed in a way that it allows potential beneficiaries to appeal after selection if they believe that they meet the eligibility criteria. Policies directed toward the promotion of a stronger civil society and empowerment of local communities can help achieve a fairer and effective appeal process. Such a process can also improve the program management as it unfolds. Targeting can be a politically sensitive issue; the system developed does not take into account the reality that policy makers, program managers, or development practitioners may adjust eligibility criteria due to political, administrative, budgetary, or other reasons.

Though the models developed have proven their validity, there is scope for further improvements. They remain to be tested for robustness across time and space. Therefore, more could be learned with additional validations if suitable data were available. These validations could also shed some light on the model validity across time given that potential structural changes could occur in the socio-political context and the household consumption behavior (e.g. changes in tastes, preferences, etc.). Likewise, this research considers the budget available for targeting the poor as exogenously determined. It does not consider the implications of financing targeted programs through the taxation of non-poor.

This research provides a framework for developing and evaluating a simple system for reaching the poor and smallholder farmers in Malawi, but the methodology can also be employed in other areas of applied research and replicated in other developing countries with similar targeting problems. In designing future tests, researchers should ensure that targeting criteria are grounded to the local perceptions of poverty. One preliminary step in designing such tests could be a qualitative survey on household perceptions of poverty and welfare in order to select the most important indicators for the purpose of the research. Subsequently, representative data should be collected on these poverty indicators to develop the proxy means test models.

A number of other potential estimation methods can be explored to develop proxy means test models. These include: Classification and Regression Trees (CART), Support Vector Machines (SVM), neural networks, etc. Reducing poverty requires first identifying the poor. However, the proxy indicator system developed is not sufficient. It must also be coupled with investments in education, rural infrastructure, economic growth related sectors, and strong political will to impact on the welfare of Malawians.

APPENDICES

Appendix 1. Sample size and number of potential indicators by model types and estimation methods

Sub-samples	Rural model	Urban model	Total
Total sample size	9,840	1,440	11,280
Calibration sample (2/3 observations)	6,560	960	7,540
Validation sample (1/3 observations)	3,280	480	3,760
Number of indicators			
Weighted Least Square Regression	148	112	-
Weighted Logit Regression	148	112	-
Weighted Logit Regression with categorical predictors only	98	79	-
Weighted Quantile Regression	148	112	-

Source: Own results based on Malawi IHS2 data. All estimations include seven regional dummies for the rural model and three city dummies for the urban model.

Appendix 2. Descriptive statistics of variables used in the rural model (full sample)

Variable label	Minimum	Maximum	Mean	Median	Standard Deviation
Full sample (9,840 observations)					
Logarithm of per capita daily expenditures	1.36	7.25	3.86	3.83	0.62
Agricultural development district is Karonga	0	1	0.05	0	0.21
Agricultural development district is Mzuzu	0	1	0.10	0	0.30
Agricultural development district is Kasungu	0	1	0.12	0	0.33
Agricultural development district is Salima	0	1	0.05	0	0.23
Agricultural development district is Lilongwe	0	1	0.21	0	0.41
Agricultural development district is Machinga	0	1	0.20	0	0.40
Agricultural development district is Blantyre	0	1	0.20	0	0.40
Agricultural development district is Ngabu	0	1	0.07	0	0.26
Household size	1	27	4.57	4	2.34
Number of members who can read in English	0	9	0.87	0	1.2
Highest educational qualification acquired in household is Junior Certificate of Education (JCE)	0	1	0.10	0	0.31
Household head can read in Chichewa	0	1	0.62	1	0.48
Number of male adults in the household	0	8	1.08	1	0.82
Household grew tobacco in past five cropping seasons	0	1	0.20	0	0.40
Floor of main dwelling is predominantly made of smooth cement	0	1	0.14	0	0.34
Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0	16	2.50	2	1.30
Any household member sleeps under a bed net?	0	1	0.37	0	0.48
Cooking fuel is collected firewood	0	1	0.84	1	0.36
Bed ownership	0	1	0.27	0	0.44
Tape, CD player, or HiFi ownership	0	1	0.12	0	0.33
Electric, gas stove, or hot plate ownership	0	1	0.01	0	0.09
Bicycle ownership	0	1	0.38	0	0.49
Paraffin lantern ownership	0	1	0.64	1	0.48
Panga ownership	0	1	0.30	0	0.46
Wireless radio ownership	0	1	0.55	1	0.49
Lighting fuel is electricity	0	1	0.02	0	0.14
Rubbish disposal facility is public rubbish heap	0	1	0.19	0	0.39

Source: Own results based on Malawi IHS2 data. Panga is a large heavy knife used for cutting the vegetation.

Appendix 3. Descriptive statistics of variables used in the rural model (calibration sample)

Variable label	Minimum	Maximum	Mean	Median	Standard Deviation
Calibration sample (6,560 observations)					
Logarithm of per capita daily expenditures	1.36	7.25	3.87	3.83	0.61
Agricultural development district is Karonga	0	1	0.05	0	0.22
Agricultural development district is Mzuzu	0	1	0.10	0	0.30
Agricultural development district is Kasungu	0	1	0.12	0	0.33
Agricultural development district is Salima	0	1	0.06	0	0.23
Agricultural development district is Lilongwe	0	1	0.21	0	0.41
Agricultural development district is Machinga	0	1	0.20	0	0.40
Agricultural development district is Blantyre	0	1	0.20	0	0.40
Agricultural development district is Ngabu	0	1	0.07	0	0.26
Household size	1	18	4.61	4	2.33
Number of members who can read in English	0	8	0.87	0	1.20
Highest educational qualification acquired in household is Junior Certificate of Education (JCE)	0	1	0.10	0	0.30
Household head can read in Chichewa	0	1	0.62	1	0.48
Number of male adults in the household	0	8	1.08	1	0.82
Household grew tobacco in past five cropping seasons	0	1	0.20	0	0.40
Floor of main dwelling is predominantly made of smooth cement	0	1	0.14	0	0.34
Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0	16	2.52	2	1.32
Any household member sleeps under a bed net?	0	1	0.37	0	0.48
Cooking fuel is collected firewood	0	1	0.84	1	0.36
Bed ownership	0	1	0.27	0	0.44
Tape, CD player, or HiFi ownership	0	1	0.12	0	0.33
Electric, gas stove, or hot plate ownership	0	1	0.01	0	0.09
Bicycle ownership	0	1	0.38	0	0.49
Paraffin lantern ownership	0	1	0.65	1	0.48
Panga ownership	0	1	0.30	0	0.46
Wireless radio ownership	0	1	0.54	1	0.50
Lighting fuel is electricity	0	1	0.02	0	0.14
Rubbish disposal facility is public rubbish heap	0	1	0.18	0	0.39

Source: Own results based on Malawi IHS2 data. Panga is a large heavy knife used for cutting the vegetation.

Appendix 4. Descriptive statistics of variables used in the rural model (validation sample)

Variable label	Minimum	Maximum	Mean	Median	Standard Deviation
Validation sample (3,280 observations)					
Logarithm of per capita daily expenditures	2.00	6.76	3.87	3.83	0.63
Agricultural development district is Karonga	0	1	0.05	0	0.22
Agricultural development district is Mzuzu	0	1	0.10	0	0.30
Agricultural development district is Kasungu	0	1	0.12	0	0.33
Agricultural development district is Salima	0	1	0.05	0	0.22
Agricultural development district is Lilongwe	0	1	0.22	0	0.41
Agricultural development district is Machinga	0	1	0.20	0	0.40
Agricultural development district is Blantyre	0	1	0.20	0	0.40
Agricultural development district is Ngabu	0	1	0.07	0	0.26
Household size	1	27	4.50	4	2.34
Number of members who can read in English	0	9	0.86	0	1.19
Highest educational qualification acquired in household is Junior Certificate of Education (JCE)	0	1	1.1	0	0.31
Household head can read in Chichewa	0	1	0.62	1	0.49
Number of male adults in the household	0	6	1.07	1	0.81
Household grew tobacco in past five cropping seasons	0	1	0.20	0	0.40
Floor of main dwelling is predominantly made of smooth cement	0	1	0.13	0	0.34
Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0	13	2.46	2	1.27
Any household member sleeps under a bed net?	0	1	0.37	0	0.48
Cooking fuel is collected firewood	0	1	0.83	1	0.37
Bed ownership	0	1	0.27	0	0.44
Tape, CD player, or HiFi ownership	0	1	0.13	0	0.33
Electric, gas stove, or hot plate ownership	0	1	0.01	0	0.09
Bicycle ownership	0	1	0.39	0	0.49
Paraffin lantern ownership	0	1	0.63	1	0.48
Panga ownership	0	1	0.31	0	0.46
Wireless radio ownership	0	1	0.57	1	0.50
Lighting fuel is electricity	0	1	0.02	0	0.14
Rubbish disposal facility is public rubbish heap	0	1	0.19	0	0.39

Source: Own results based on Malawi IHS2 data. Panga is a large heavy knife used for cutting the vegetation.

Appendix 5. Descriptive statistics of variables used in the urban model (full sample)

Variable label	Minimum	Maximum	Mean	Median	Standard Deviation
Full sample (1,440 observations)					
Logarithm of per capita daily expenditures	2.53	7.65	4.45	4.36	0.81
Mzuzu city	0	1	0.17	0	0.37
Lilongwe city	0	1	0.33	0	0.47
Zomba city	0	1	0.17	0	0.37
Blantyre city	0	1	0.33	0	0.47
Household size	1	15	4.36	4	2.32
Number of members who can read in English	0	12	1.83	1	1.81
Household head can read in Chichewa	0	1	0.85	1	0.36
Highest class level ever attended by females in the household is secondary/post primary	0	1	0.31	0	0.46
Highest class level ever attended by members is superior or post-secondary	0	1	0.08	0	0.28
Household has a cellular phone in working condition	0	1	0.17	0	0.38
Household owns a landline telephone in working condition	0	1	0.05	0	0.22
Cooking fuel is collected firewood	0	1	0.15	0	0.35
Lighting fuel is electricity	0	1	0.32	0	0.47
Bed ownership	0	1	0.67	1	0.47
Television & VCR ownership	0	1	0.18	0	0.39
Electric, gas stove, or hot plate ownership	0	1	0.15	0	0.35
Sewing machine ownership	0	1	0.04	0	0.20
Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0	10	2.53	2	1.28
Dwelling construction material is traditional	0	1	0.21	0	0.41
Household head sleeps on Mat (grass) on floor	0	1	0.27	0	0.44
Household has no toilet facility	0	1	0.03	0	0.17
Floor of main dwelling is predominantly made of smoothed cement	0	1	0.63	1	0.48
Is there a place to purchase common medicines, such as panadol in this community?	0	1	0.93	1	0.25

Source: Own results based on Malawi IHS2 data.

Appendix 6. Descriptive statistics of variables used in the urban model (calibration sample)

Variable label	Minimum	Maximum	Mean	Median	Standard Deviation
Calibration sample (960 observations)					
Logarithm of per capita daily expenditures	2.53	7.50	4.48	4.37	0.83
Mzuzu city	0	1	0.17	0	0.37
Lilongwe city	0	1	0.33	0	0.47
Zomba city	0	1	0.17	0	0.37
Blantyre city	0	1	0.33	0	0.47
Household size	1	15	4.24	4	2.26
Number of members who can read in English	0	10	1.72	1	1.69
Household head can read in Chichewa	0	1	0.84	1	0.36
Highest class level ever attended by females in the household is secondary/post primary	0	1	0.30	0	0.46
Highest class level ever attended by members is superior or post-secondary	0	1	0.09	0	0.28
Household has a cellular phone in working condition	0	1	0.17	0	0.37
Household owns a landline telephone in working condition	0	1	0.05	0	0.22
Cooking fuel is collected firewood	0	1	0.14	0	0.35
Lighting fuel is electricity	0	1	0.31	0	0.46
Bed ownership	0	1	0.67	1	0.47
Television & VCR ownership	0	1	0.16	0	0.37
Electric, gas stove, or hot plate ownership	0	1	0.14	0	0.34
Sewing machine ownership	0	1	0.05	0	0.21
Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	1	10	2.53	2	1.31
Dwelling construction material is traditional	0	1	0.22	0	0.41
Household head sleeps on Mat (grass) on floor	0	1	0.27	0	0.44
Household has no toilet facility	0	1	0.02	0	0.15
Floor of main dwelling is predominantly made of smoothed cement	0	1	0.63	1	0.48
Is there a place to purchase common medicines, such as panadol in this community?	0	1	0.93	1	0.25

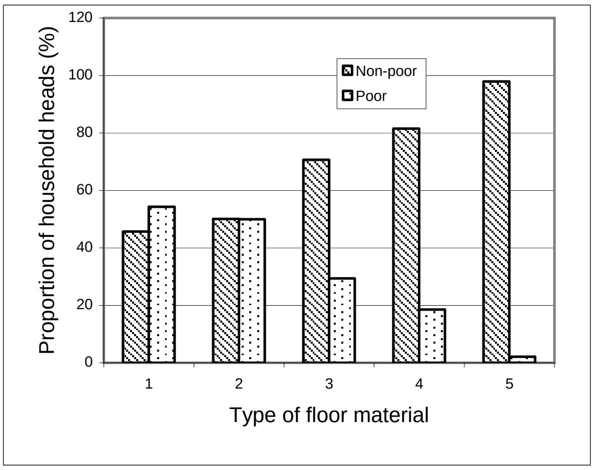
Source: Own results based on Malawi IHS2 data.

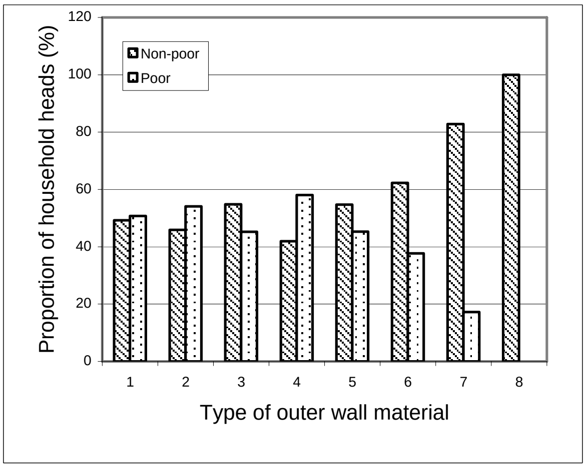
Appendix 7. Descriptive statistics of variables used in the urban model (validation sample)

Variable label	Minimum	Maximum	Mean	Median	Standard Deviation
Validation sample (480 observations)					
Logarithm of per capita daily expenditures	2.64	7.65	4.40	4.35	0.77
Mzuzu city	0	1	0.17	0	0.37
Lilongwe city	0	1	0.33	0	0.47
Zomba city	0	1	0.17	0	0.37
Blantyre city	0	1	0.33	0	0.47
Household size	1	14	4.62	4	2.41
Number of members who can read in English	0	1	2.04	2	2.01
Household head can read in Chichewa	0	1	0.86	1	0.35
Highest class level ever attended by females in the household is secondary/post primary	0	1	0.32	0	0.47
Highest class level ever attended by members is superior or post-secondary	0	1	0.08	0	0.27
Household has a cellular phone in working condition	0	1	0.19	0	0.39
Household owns a landline telephone in working condition	0	1	0.05	0	0.21
Cooking fuel is collected firewood	0	1	0.15	0	0.36
Lighting fuel is electricity	0	1	0.35	0	0.48
Bed ownership	0	1	0.67	1	0.47
Television & VCR ownership	0	1	0.22	0	0.41
Electric, gas stove, or hot plate ownership	0	1	0.16	0	0.37
Sewing machine ownership	0	1	0.04	0	0.19
Number of separate rooms occupied by household, excluding toilet, storeroom, or garage	0	8	2.52	2	1.23
Dwelling construction material is traditional	0	1	0.20	0	0.40
Household head sleeps on Mat (grass) on floor	0	1	0.28	0	0.45
Household has no toilet facility	0	1	0.04	0	0.20
Floor of main dwelling is predominantly made of smoothed cement	0	1	0.62	1	0.49
Is there a place to purchase common medicines, such as panadol in this community?	0	1	0.93	1	0.26

Source: Own results based on Malawi IHS2 data.

Appendix 8. Household housing conditions

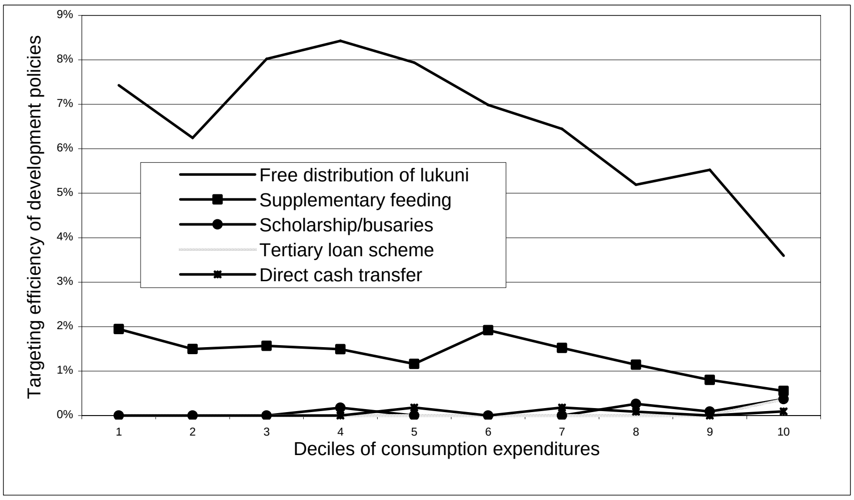




Source: Own results based on Malawi IHS2 data.

Type of floor material: 1=sand, 2=smoothed mud, 3=wood, 4=smoothed cement, 5=tile.
Material of outer wall: 1=grass, 2=mud “yomata”, 3=compacted earth “yamdindo”, 4=wood, 5=mud brick unfired, 6=burnt bricks, 7=concrete, 8=iron sheets.

Appendix 9. Targeting efficiency of development policies



Source: Own results based on Malawi IHS2 data.

Appendix 10. Urban model's results under different methods

Poverty line	Method	Cut-off values (MK)	Poverty accuracy (%)	Under-coverage (%)	Leakage (%)	PIE (% points)	BPAC (% points)
National	***WLS***	3.92	**62.16** (53.3; 71.0)	**37.84** (29.0; 46.7)	**38.74** (26.3; 52.8)	**0.21** (-3.5; 3.8)	**61.26** (40.9; 66.5)
	WL	0.39	**61.26** (51.7; 70.5)	**38.74** (29.5; 48.3)	**39.64** (27.3; 53.5)	**0.21** (-3.2; 4.0)	**60.36** (40.9; 66.0)
	WL categorical	20	**63.96** (55.0; 72.3)	**36.04** (27.7; 45.0)	**36.94** (24.8; 52.0)	**0.21** (-3.5; 3.8)	**63.06** (42.9; 67.7)
	W Quantile	3.63	**60.36** (51.5; 69.2)	**39.64** (30.8; 48.5)	**48.65** (34.3; 67.3)	**2.08** (-1.9; 6.2)	**51.35** (32.7; 62.9)
International	***WLS***	4.18	**74.57** (68.3; 81.2)	**25.43** (18.8; 37.1)	**24.86** (17.4; 34.2)	**-0.21** (-3.8; 3.7)	**73.99** (59.5; 77.6)
	WL	0.43	**73.99** (67.7; 79.9)	**26.01** (20.1; 32.3)	**26.59** (18.6; 36.2)	**0.21** (-3.6; 4.0)	**73.41** (59.5; 76.6)
	WL categorical	22	**76.30** (69.9; 82.5)	**23.70** (17.5; 30.1)	**27.17** (19.2; 36.9)	**1.25** (-2.5; 5.4)	**72.83** (62.0; 77.6)
	W Quantile	4.06	**78.04** (71.8; 84.0)	**21.97** (16.0; 28.2)	**34.10** (24.2; 44.5)	**4.38** (-0.2; 8.1)	**65.90** (55.5 ; 74.9)
Extreme	***WLS***	3.52	**50** (31.8; 67.7)	**50** (32.3; 68.2)	**73.53** (43.7; 123.0)	**1.67** (-0.8; 4.2)	**26.47** (-23.4; 50.5)
	WL	0.30	**47.06** (31.0; 64.7)	**52.94** (35.3; 69.0)	**61.77** (32.1; 104.4)	**0.63** (-1.9; 3.1)	**38.23** (-5.61; 51.7)
	WL scorecard	8	**64.71** (43.4; 80.0)	**35.29** (20.0; 52.6)	**94.12** (57.6; 152.0)	**4.17** (1.7; 7.1)	**5.88** (-52.0; 42.0)
	W Quantile	2.93	**47.06** (29.1; 65)	**52.94** (35; 70.9)	**73.53** (40.5; 123.8)	**1.46** (-1.3; 4.2)	**26.47** (-22.8; 50.0)

Source: Own computations based on Malawi IHS2 data. Bootstrapped prediction intervals in brackets. Cut-off values are expressed in Logarithm MK under the WLS and probability for the WL. PIE is defined as the Poverty Incidence Error. BPAC is defined as the Balanced Poverty Accuracy Criterion.

AUTHOR'S DECLARATION

I hereby declare that this research is my original and independent work. No aids other than the indicated resources have been used herein. This work has not been previously used neither completely nor in parts for achieving any other academic degree.

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