OXFORD POVERTY & HUMAN DEVELOPMENT INITIATIVE
www.ophi.org.uk

UNIVERSITY OF OXFORD

Summer School on Multidimensional Poverty Analysis

11–23 August 2014

Oxford Department of International Development
Queen Elizabeth House, University of Oxford

Tabita, Kenya — Rabiya, India — Stéphanie, Madagascar — Agatha, Madagascar — Dalma, Kenya — Ann-Sophia, Kenya — Valérie, Madagascar

OPHI

OXFORD POVERTY & HUMAN DEVELOPMENT INITIATIVE

www.ophi.org.uk

UNIVERSITY OF OXFORD

Targeting and Impact Evaluation

Sabina Alkire and Ana Vaz

21 August 2014

Oxford University, UK

Tabita, Kenya | Rabiya, India | Stephanie, Madagascar | Agathe, Madagascar | Dalma, Kenya | Ann-Sophia, Kenya | Valérie, Madagascar

Outline

Multidimensional Targeting

Multidimensional Impact Evaluation

Tabita, Kenya | Rabiya, India | Stéphanie, Madagascar | Agatha, Madagascar | Dalma, Kenya | Ann-Sophia, Kenya | Valérie, Madagascar

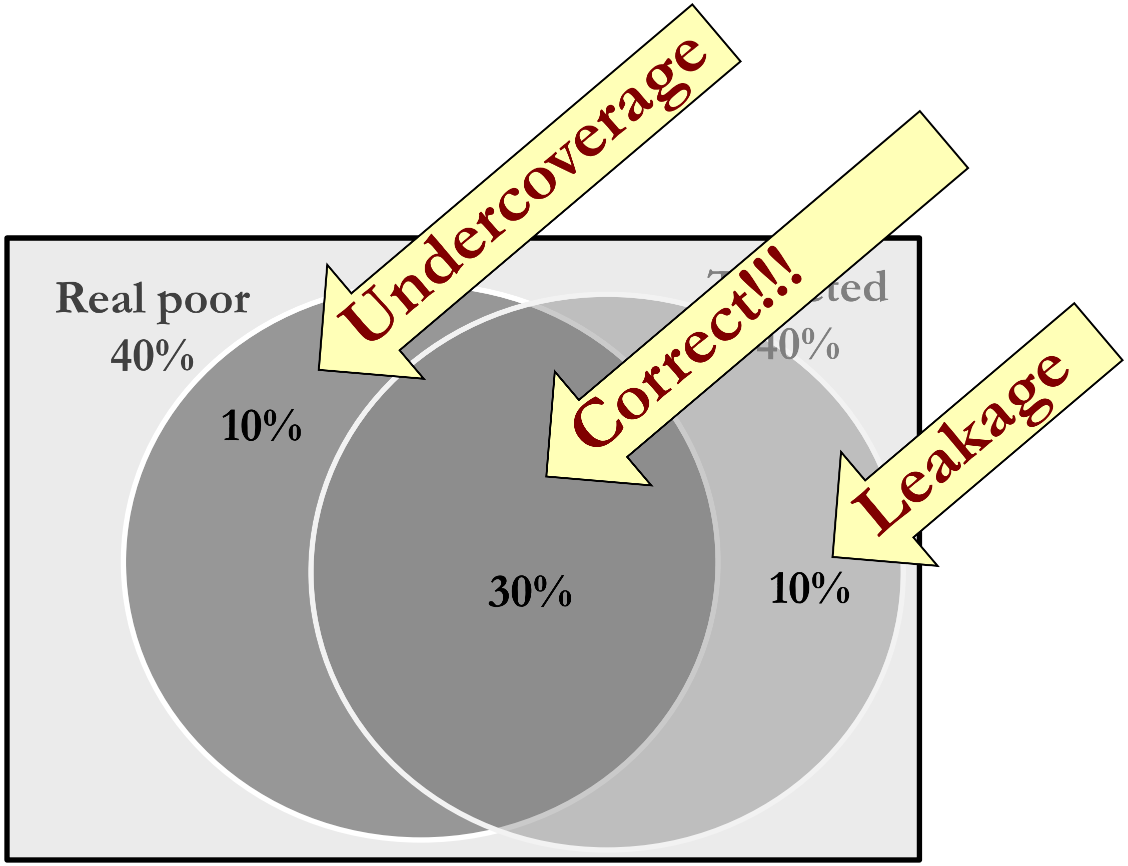
Multidimensional Targeting

The Challenge of Targeting

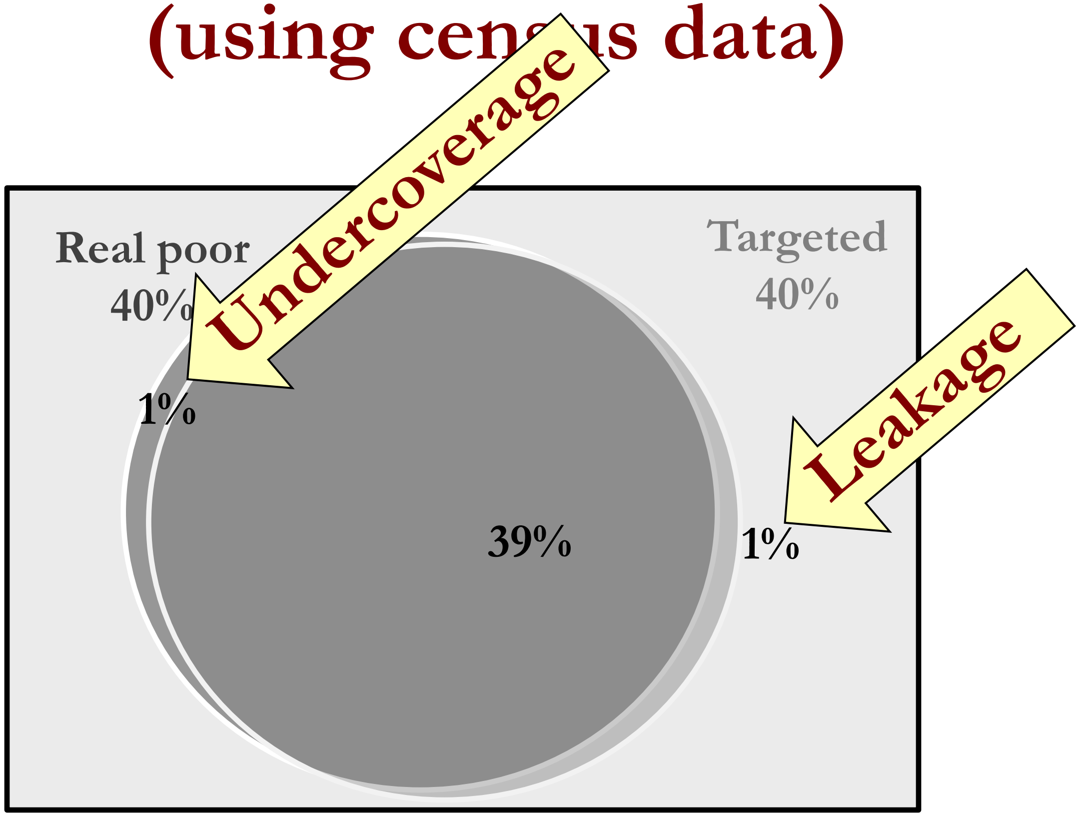
To simplify greatly, targeting methods must:

1. Identify poor people relatively accurately
2. Use census-based indicators that:
   a. are inexpensive to collect
   b. are accurate or can be verified
   c. do not create perverse incentives
3. Use a simple, transparent method, which enables cross-checking by other actors (at least in some contexts).

The Challenge of Targeting



The Challenge of Targeting
(minimize undercoverage/leakage)
(using census data)



The Challenge of Targeting

Proxy means tests: sufficient accuracy?

Using cross-country simulations, for **30%** eligibility threshold, Grosh and Baker (1995) finds that the under-coverage rate and leakage rate in urban Jamaica to be **43%** and **26.1%,** respectively. The corresponding rates are **39.3**% and **24.1**% for urban Bolivia, and **53.8**% and **35.1**% for urban Peru.

Narayan and Yoshida (2005), in case of Sri Lanka, find that the under-coverage rate and the leakage rate for the model with best predicting power to be **28**% and **31**% for the 40th cutoff percentile **Can this improve?**

Resources on AF & Targeting

Robano, V. & Smith, S. C. (2014) "Multidimensional targeting and evaluation: A general framework with an application to a poverty program in Bangladesh." *OPHI Working Paper* 65.

Alkire and Seth (2013). "Selecting a Targeting Method to Identify BPL Households in India." *Social Indicators Research* 112(2) 417-446

Azevado and Robles (2013). "Multidimensional Targeting: Identifying Beneficiaries of Conditional Cash Transfer Programs", *Social Indicators Research*. 112(2).

This is an area of ongoing investigation & development

Proposal

The Targeting method should be the best proxy of **direct measures** of poverty with good data

- National MPI can **track reduction** in poverty and celebrate progress
- National MPI should reflect **policy priorities**.
- Identification of 'who is poor' is a **normative** choice, so targets should be linked to an 'anchor' measure
- **Census** data will be imperfect
- A simple structure may be needed for **transparency**

How identify 'target group'? Start with official National MPI

The 'anchor' measure would be a national MPI.

The national MPI reflects values and policy priorities – the purpose of the measure – drawing on good survey data.

The national MPI is updated regularly, and analysed by region, rural/urban, and other population subgroups.

The national MPI shows changes over time – including those that are the outcome of targeted interventions.

How identify 'target group'? Census-based MPI_T

Construct an MPI_T based on census to identify target population.

Design the MPI_T to identify the MPI poor

The choice of MPI_T parameters (indicators, weights, cutoffs) are justified by providing the closest proxy to MPI identification of who is poor.

Requires a survey including census & MPI survey questions.

Note: Census questions

Census schedules used for targeting differ from surveys:

- **Simpler** (appropriate for less specialized enumerators)
  - E.g. malnutrition,
- **Shorter** (less costly per person but less precise)
  - E.g. household roster
- **Visible & Verifiable** (to minimize error/misreporting)
  - E.g. income vs housing
- **Consider incentives** (so don't distort behaviours)
  - E.g. sanitation

Note: Census questions

By implication, available and appropriate questions differ:

- **More use of proxy variables**
  - E.g. caste
- **More emphasis on identification, less on trends**
  - E.g. exclusion criteria
- **Transparency needs vary**
  - E.g. simple (counting) vs undisclosed

Requirements to design targeting instrument:

Dataset that includes:

- Questions for national MPI
- Questions for targeting census
- Sample that reflects relevant diversity

National MPI specifications

- To identify who is poor individually
- To establish different *levels* of poverty

Tools of Targeting

Using dataset and MPI specifications, design:

a) **Exclusion** Criteria – income tax, house, car
   - Rule out non-poor

b) **Inclusion** Criteria – indicators, group
   - Identify who is poor

c) .Some **combination** of both.

(Counting-based measures can be used for both criterion)

Adjust design to minimize leakage and undercoverage

How justify targeting method?

The chosen targeting method should be the best proxy of direct measures of people's poverty ('real poor') that use good data. Least leakage/undercov.

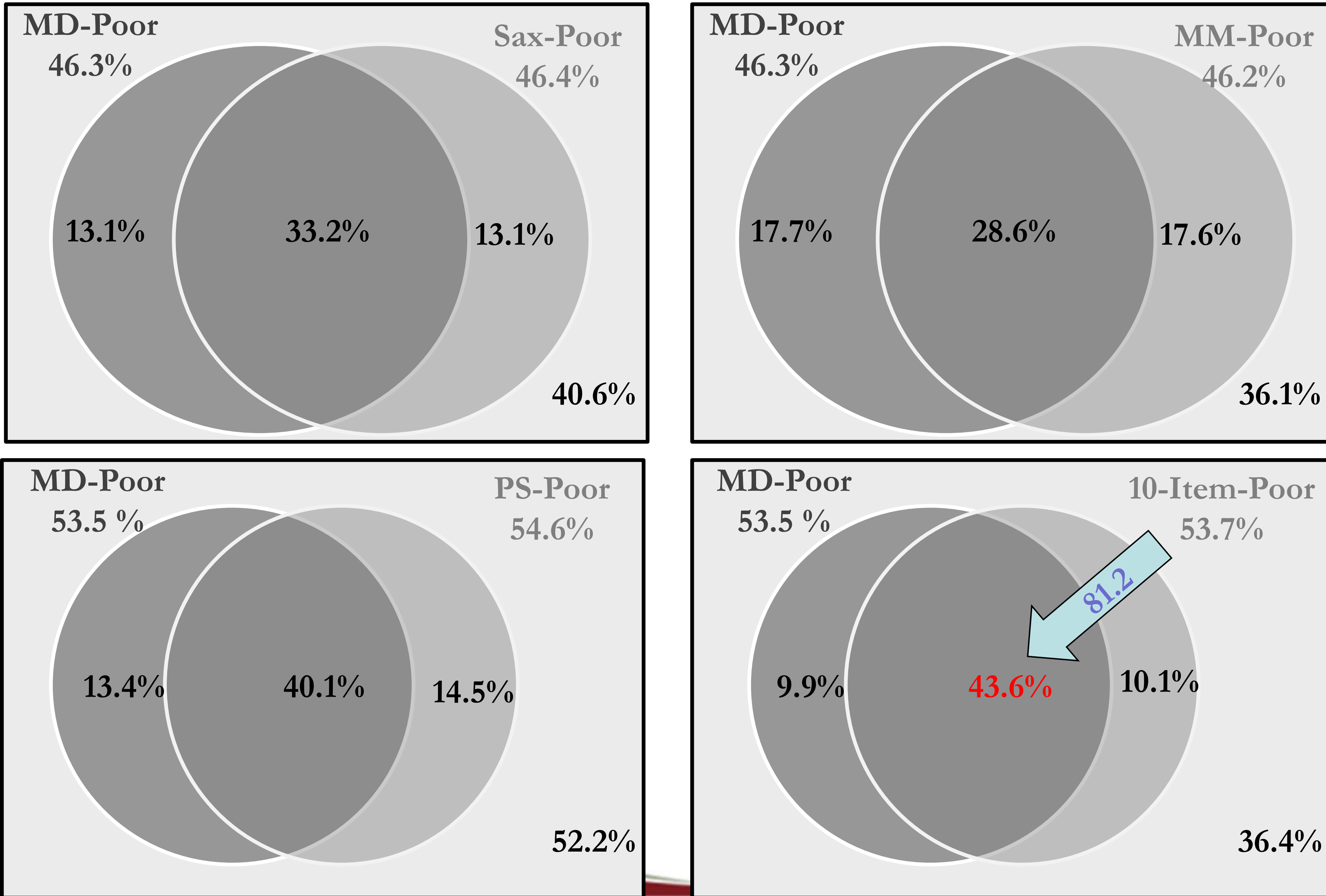
1 - census data will be approximate
2 - need to 'justify' method to public
3 - identification of 'who is poor' is a
normative choice

How justify targeting method?

The chosen targeting method should be the best proxy of direct measures of people's poverty ('real poor') that use good data. Least leakage/undercov.

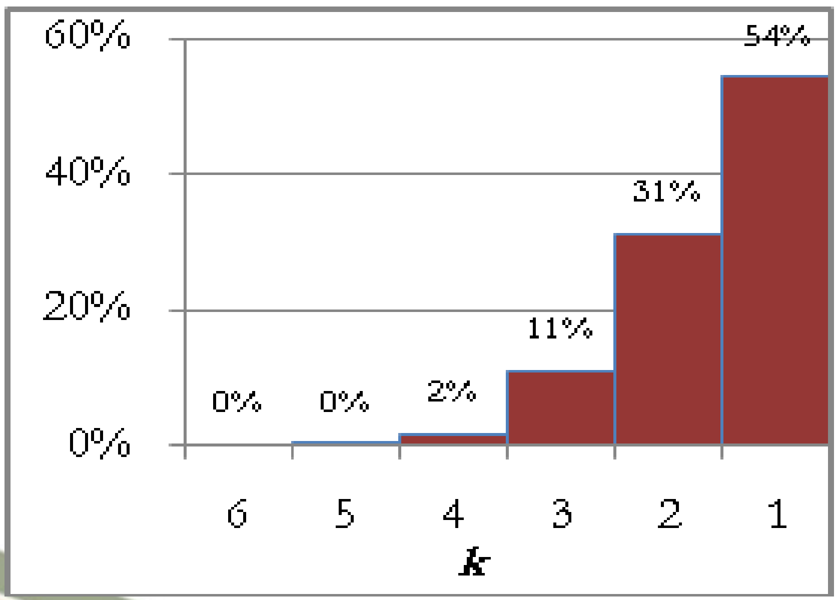
4 – not all census indicators 'direct'.
5 – MPI can track reduction in 'real' poverty over time (verifiable indicators may not show relevant trends)

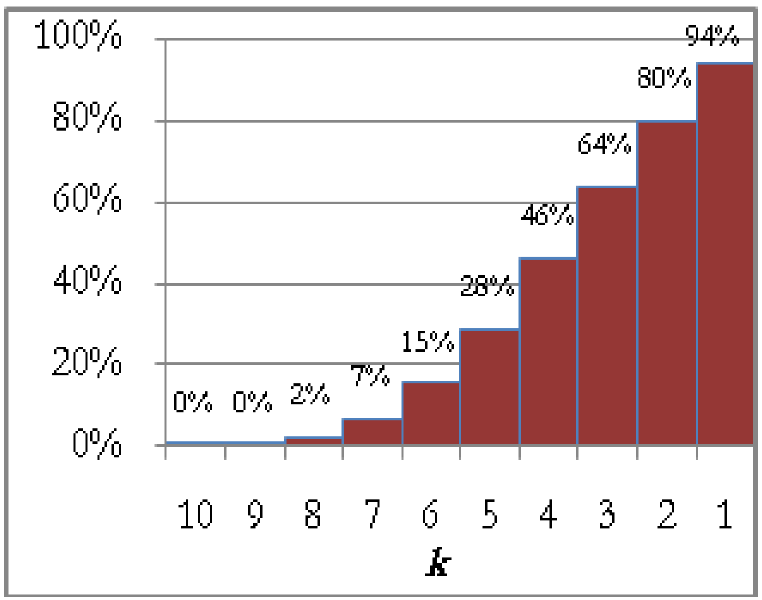
Which is the Best Proxy?



How Many Indicators? Cost/Simplicity vs Bunching

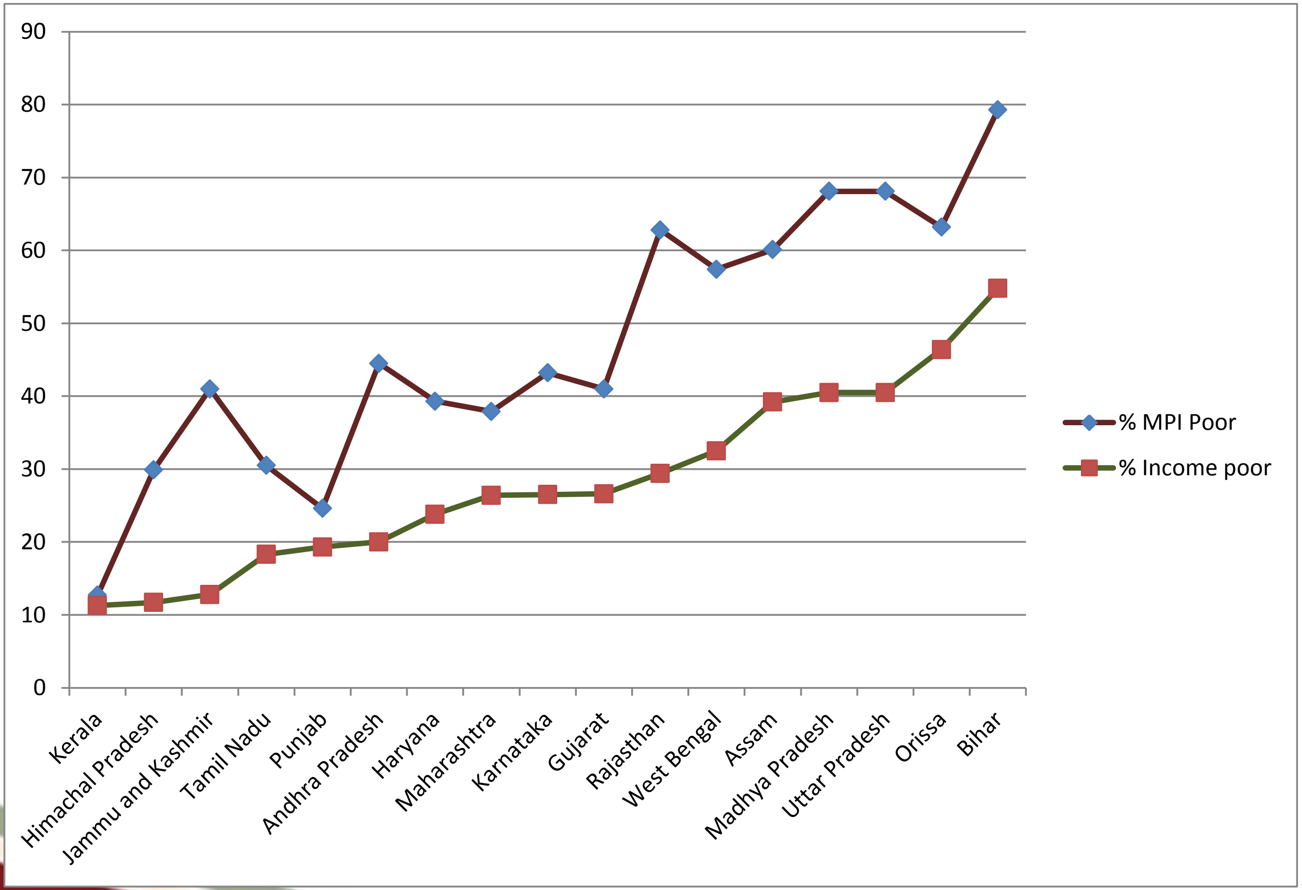
With few indicators only there will be 'bunching' issues at local/provincial levels - here up to 25%.





How many are to be targeted in each region?

State level 'caps' based on income poverty may not match multidimensional poverty 'caps'



Conclusions

A targeting exercise has distinct challenges

census data incentives leakage/uc

With the same data, a difference in targeting methodology makes a large difference empirically (literature)

A targeting method can be justified because it proxies the identification in an Multidimensional Poverty Index

The number of indicators used does affect precision.

Size of target populations (*value of regional k for* MPI_T) should reflect MPI levels based on good survey data.

Multidimensional Impact Evaluation

Motivation

- Increasing recognition that poverty is a multidimensional phenomenon.
  - "That poverty is a multidimensional phenomenon is no longer debatable." (Balisacan, 2011)

- More and more poverty reduction programs are adopting multidimensional approaches. Examples:
  - Conditional Cash Transfers (Bouillon & Yanez-Pagans, 2011).
  - Millennium Villages Project

Motivation

- Growing importance of impact/program evaluation
  - Provides evidence of what works:
    - "essential instrument to test the validity of specific approaches to development and poverty alleviation" (World Bank)
    - "We want to fund things that work" (Boorstin, Deputy Director of Bill and Melinda Gates Foundation, at UN Summit in New York 2010)
  - Is "an accountability tool at the end of a project cycle" (Dr. Kremer, at UN Summit in New York 2010)

- So, it seems natural that the targeting and evaluation of poverty reduction programs with a multidimensional approach should also be multidimensional.

Purpose

- Show how the Alkire Foster (AF) methodology can be used in impact evaluation
- Empirical application using the case of *Oportunidades* in rural areas

Background

- There is already literature that links the AF methodology with the targeting of poverty reduction interventions
  – Bouillon & Yanez-Pagans, 2011;
  – Alkire & Seth, 2013;
  – Azevedo & Robles, 2013;
  – Robano & Smith, 2014.

- As far as I know, only one study has explored the use of AF methodology for impact evaluation
  – Robano & Smith, 2014

Why use the AF methodology?

- More direct measure of the overall program's performance
- It allows us to monitor the impact of programs on the:
  - Incidence of deprivations, and
  - The joint distribution of deprivations.
- Communication of results: we can summarize impact at different levels into one number

How to use the AF methodology?

- Suppose:
  - A poverty reduction program with D objectives;
  - That each objective can be defined in terms of minimum achievement thresholds, $\boldsymbol{z}$, for each target unit (person, household, community, etc.);
  - Let w_d be the weight/importance of objective d;
  - That the overall goal of the program can be defined as reducing the weighted sum of the targets' missed objectives below a certain cutoff, k.

  - We have information for the beneficiaries of the program as well as for a comparable control group.

How to use the AF methodology?

- In these circumstances, we can ‘translate’ the program’s overall goal into a M0 measure.
  - D objectives => D or plus indicators
  - z minimum achievement thresholds => z deprivation cut-offs
  - k is the program cut-off

How to use the AF methodology?

- Identification of poor based on dual cut-offs
  - Who is deprived in each indicator?
  - Who has at least k weighted deprivations/missed objectives?

- M_0 can be expressed as:

$$M_0 = H \, x \, A$$

  - Incidence (H): % of people missing the overall program goal
  - Intensity (A): % of weighted deprivations of people who are missing the overall program goal

- Fundamental property: Decomposability

How to use the AF methodology?

- Use M_0/H as the outcome of interest in the evaluation of the program's impact:
  - Compute the M_0/H for the treated and control groups;
  - Test whether the difference between the M_0/H of the two groups is statistically significant.
  - Test impact on the raw and censored headcounts
  - Test the impact on the weighted number of deprivations
  - If we also have data for multiple points of time, we can compare the change in M_0/H (Difference-in-difference estimator).

How to use the AF methodology?

- Instead of computing means, we can estimate difference-in-difference regressions and control for demographic characteristics.

- When we have data for multiple points in time, we can do additional analyses:
  - Assess groups' baseline comparability;
  - Impact on probabilities of transition;
  - Decompose change in M_0 over time:
    - Between movements in-out of poverty and intensity of ongoing poor;
    - Across different population groups / geographical areas.

Empirical application

- Why *Oportunidades*?
  - Pioneer in Conditional Cash Transfer Programs
  - Multi-sector program
    - Education
    - Health
    - Nutrition
  - Experimental design
    - Randomization of localities into control and treatment groups
    - Data collected before and after the start of the treatment

Empirical application

– Impact of *Oportunidades* in single indicators documented:
  - Positive impact on enrolment (Schultz, 2000)
  - No impact on school attendance (Schultz, 2000)
  - Significant reduction in school grade gaps (Behram, Sengupta & Todd, 2000, 2005)
  - Positive impact on the number of grades completed (Behram, Parker & Todd, 2005)
  - Increase in number of visits to public health centres (Gertler, 2000)
  - Negative impact on probability of illness of children under 5 (Gertler, 2000)
  - Negative impact on children's labor (Parker & Todd, 2000)
  - Increase in food expenditure (Hoddinott & Skoufias, 2004)

Empirical application

- Select indicators that:
  - Reflect the program's minimum goals;
  - Based on previous evaluation literature;
  - For which we have data for all time periods.

- Select weights

Empirical application

List of indicators

Indicator	Deprived if:	Weights
Enrolment	at least one member aged 6-14 not attending school	0.125
School attendance	at least one member aged 6-14 attended less than 90% of the school days (past month) OR is not enrolled	0.125
No child labor	at least one member aged 8-14 had a job or worked during last week (even if unpaid)	0.25
Children's health	at least one member aged 0-2 was ill in the past 4 weeks for more than 5 days	0.25
Health visits for nutrition monitoring	at least one member aged 0-2 has not made any visit in the past 6 months	0.25

- **Problem**: As all indicators are defined with reference to children, the poverty status of the household is highly dependent on its the demographic structure.

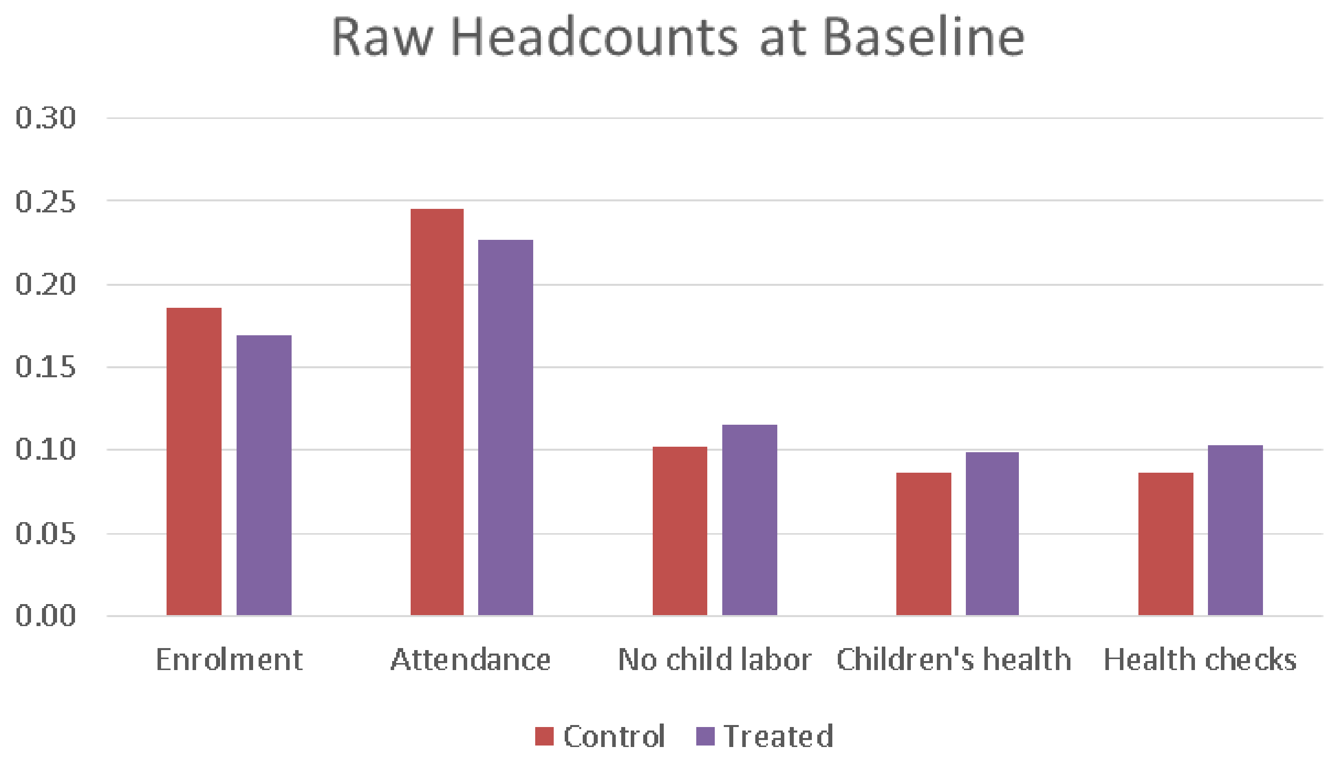
Sample

Table 1: Sample size and attrition

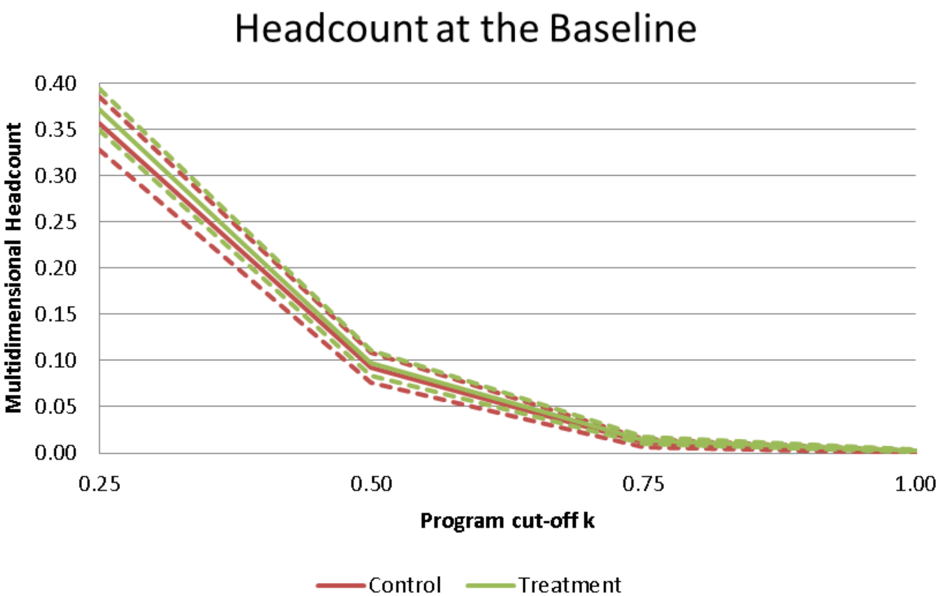
Datasets	Sample of eligible households [1]							
	Sample size				Atrition rates (%)			
	Control areas		Treatment areas		Control areas		Treatment areas	
	HH	Ind.	HH	Ind.	HH	Ind.	HH	Ind.
ENCASEH 97 + ENCEL 98 March	4,582	29,580	7,665	49,219				
ENCEL 98, October	4,735	28,683	7,895	47,492				
Panel with two time periods [2]	**4,307**	**25,226**	**7,241**	**42,232**	**6.00**	**14.72**	**5.53**	**14.20**
ENCEL 99, March	4,316	26,199	7,170	43,442				
Panel with three time periods	**3,821**	**22,159**	**6,486**	**37,688**	**16.61**	**25.09**	**15.38**	**23.43**
ENCEL 99, November	4,417	27,116	7,079	43,260				
Panel with four time periods	**3,652**	**21,048**	**6,040**	**35,032**	**20.30**	**28.84**	**21.20**	**28.82**

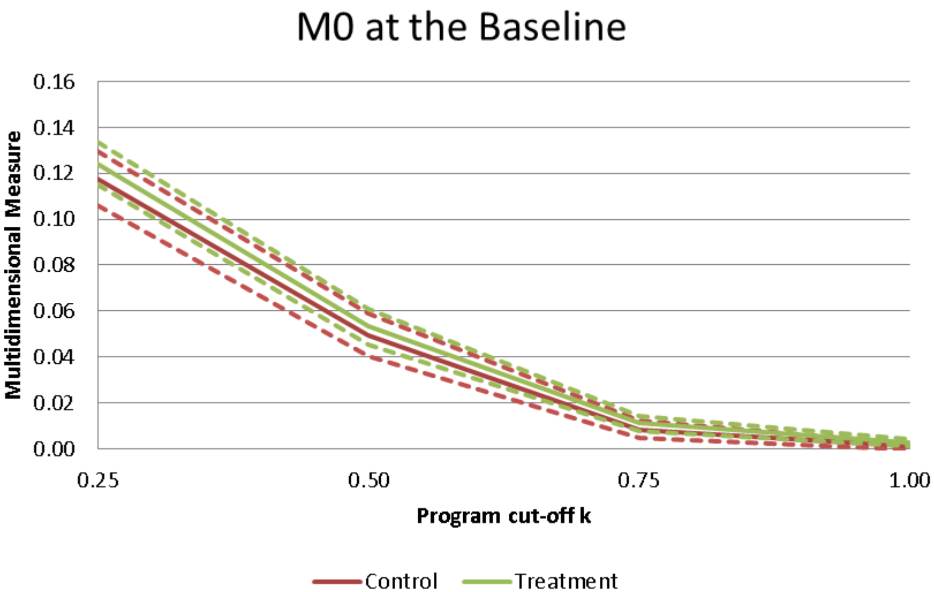
(1) Based on the original eligibility criterion, 'pobre'.

Differences at baseline?

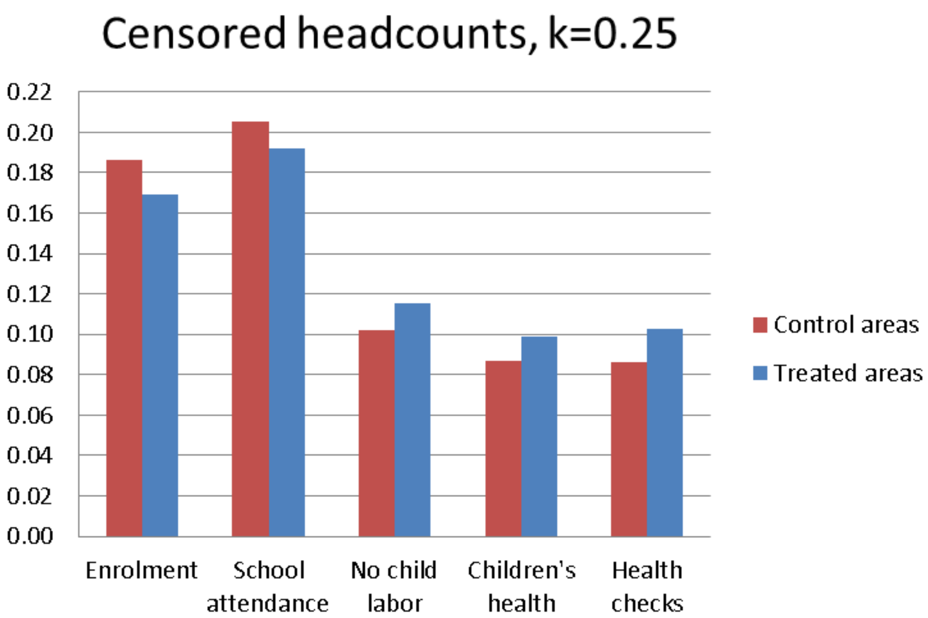


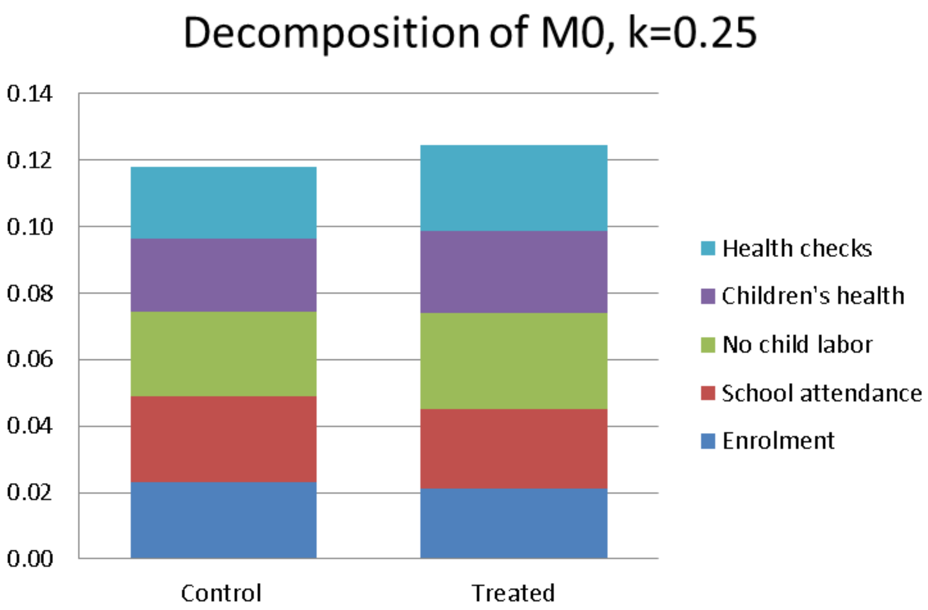
Differences at baseline?



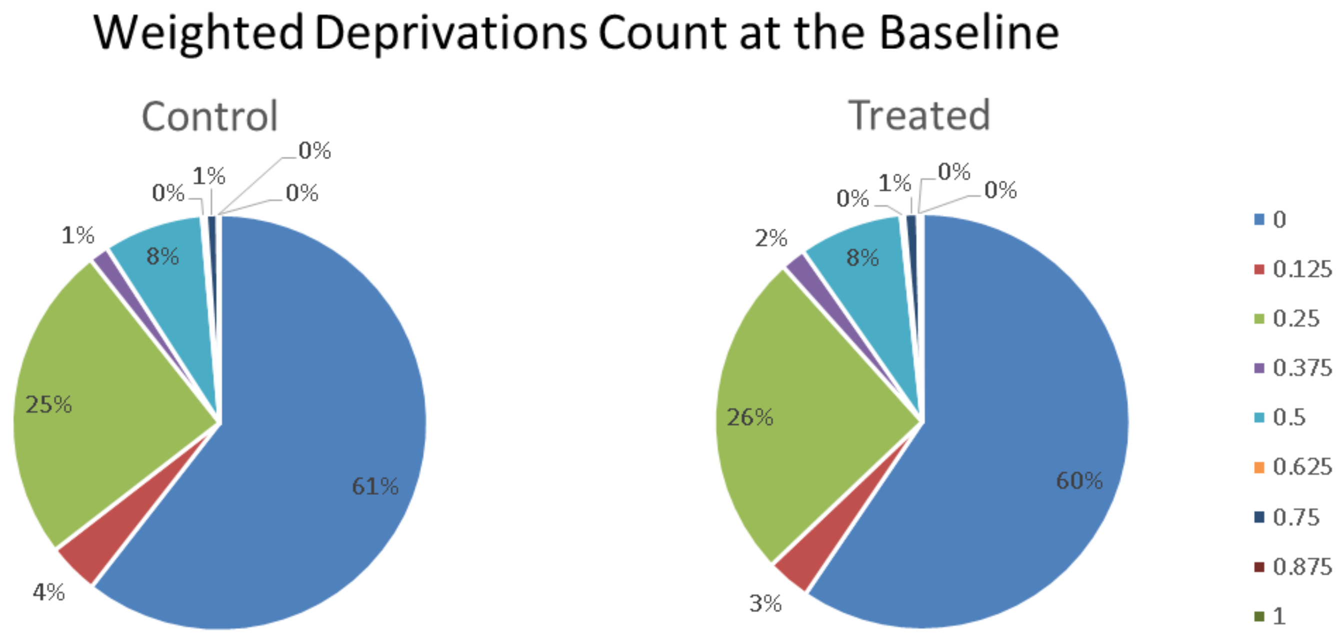


Differences at baseline?

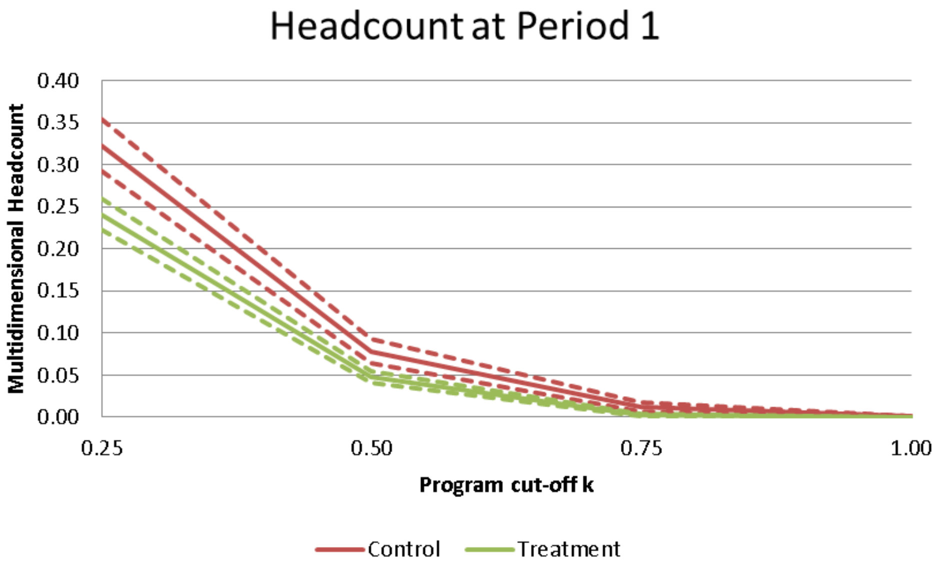


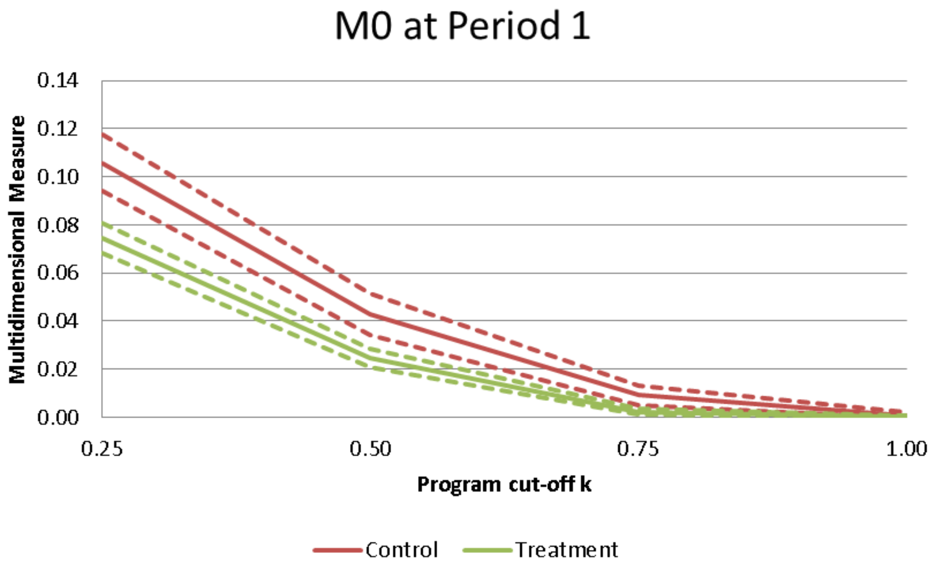


Differences at baseline?

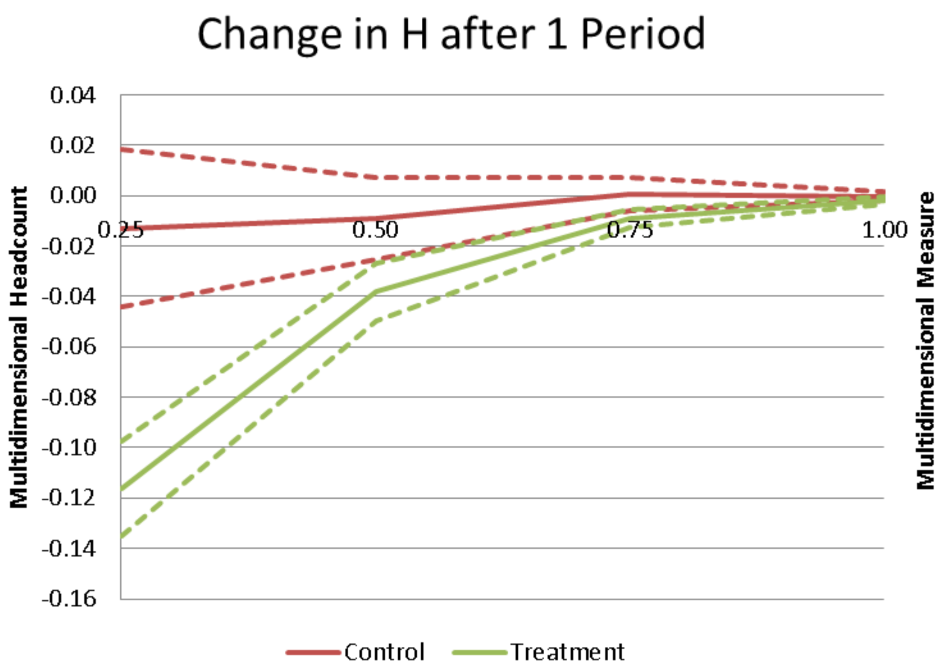


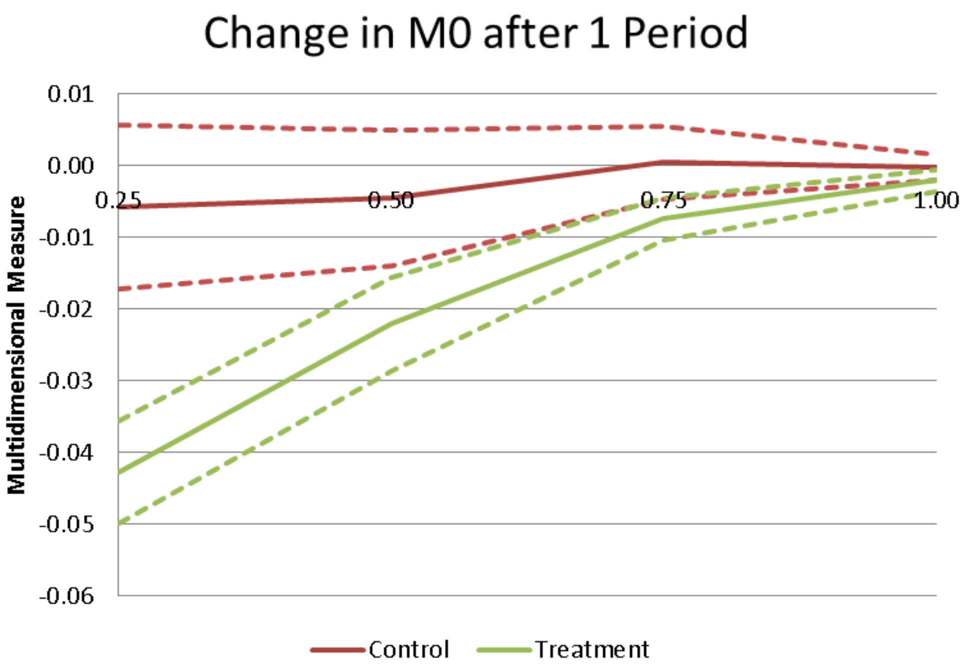
Impact – Using only cross section



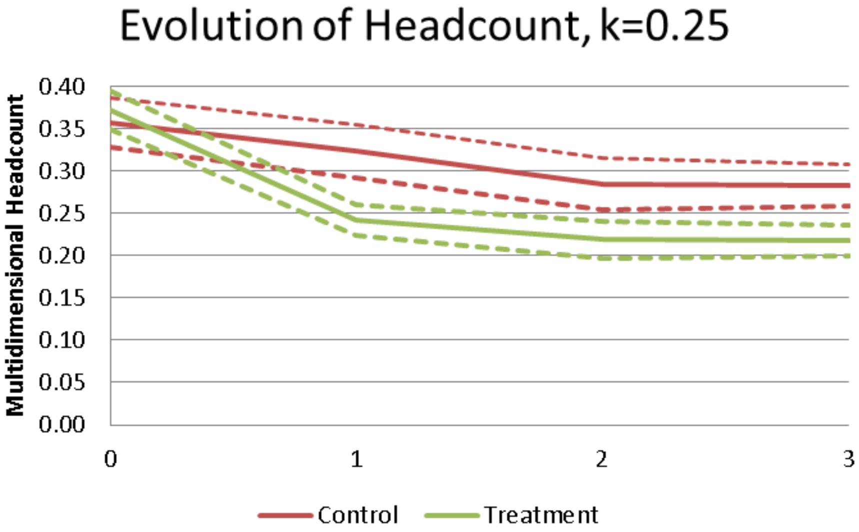


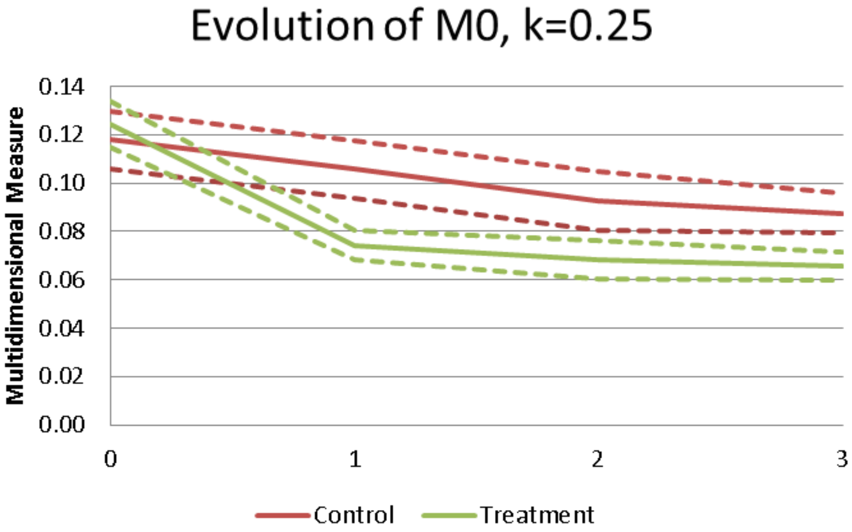
Impact – Using time series





Impact – Using time series





Impact – H and M0

Table: Program's impact considering different cutoffs

Time	Cutoff (k)	Headcount				Multidimensional Measure			
		Control	Treated	Dif.	Dif-in-Dif	Control	Treated	Dif.	Dif-in-Dif
0	0.25	0.357	0.372	0.014		0.118	0.124	0.007	
	0.50	0.092	0.098	0.005		0.050	0.053	0.004	
	0.75	0.011	0.014	0.003		0.008	0.011	0.003	
	1.00	0.001	0.003	0.002		0.001	0.003	0.002	
1	0.25	0.323	0.241	-0.082***	-0.100***	0.106	0.074	-0.031***	-0.039***
	0.50	0.079	0.047	-0.031***	-0.036***	0.043	0.025	-0.018***	-0.021***
	0.75	0.012	0.003	-0.009***	-0.012***	0.009	0.002	-0.007***	-0.009**
	1.00	0.001	0.000	-0.001	-0.002*	0.001	0.000	-0.001	-0.002*
2	0.25	0.284	0.219	-0.065***	-0.084***	0.093	0.068	-0.024***	-0.032***
	0.50	0.071	0.039	-0.032***	-0.036***	0.037	0.021	-0.016***	-0.020**
	0.75	0.004	0.004	0.000	-0.003	0.003	0.003	0.000	-0.003
	1.00	0.000	0.000	0.000	-0.002	0.000	0.000	0.000	-0.002
3	0.25	0.283	0.218	-0.065***	-0.083***	0.087	0.066	-0.022***	-0.029***
	0.50	0.061	0.041	-0.021***	-0.025**	0.032	0.021	-0.011***	-0.014**
	0.75	0.004	0.002	-0.002	-0.005	0.003	0.001	-0.002	-0.004
	1.00	0.000	0.000	0.000	-0.002*	0.000	0.000	0.000	-0.002*

Impact – Deprivations count

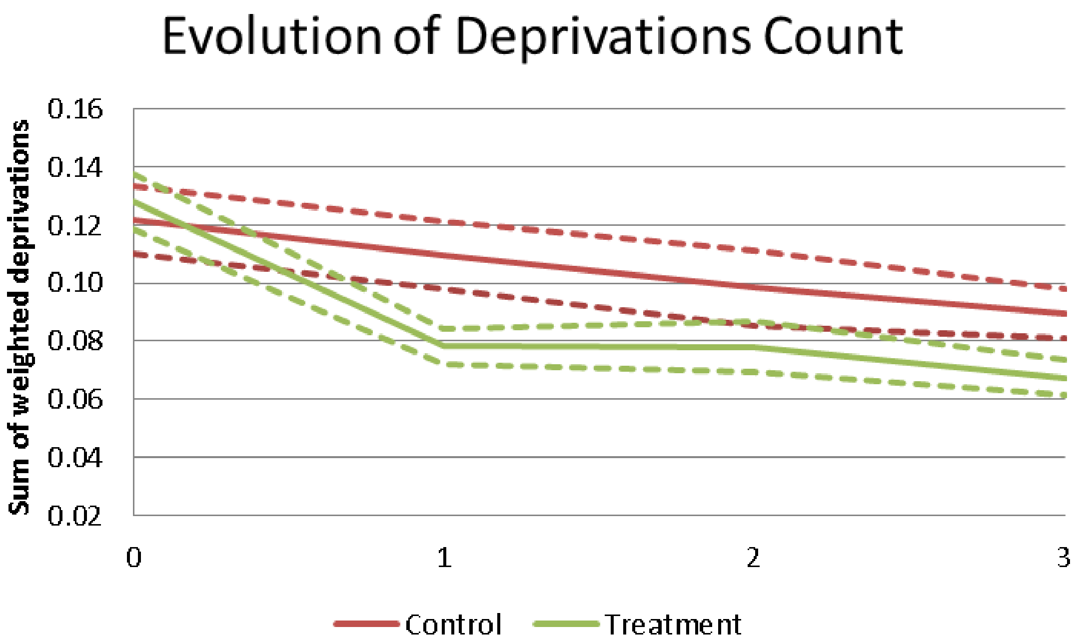
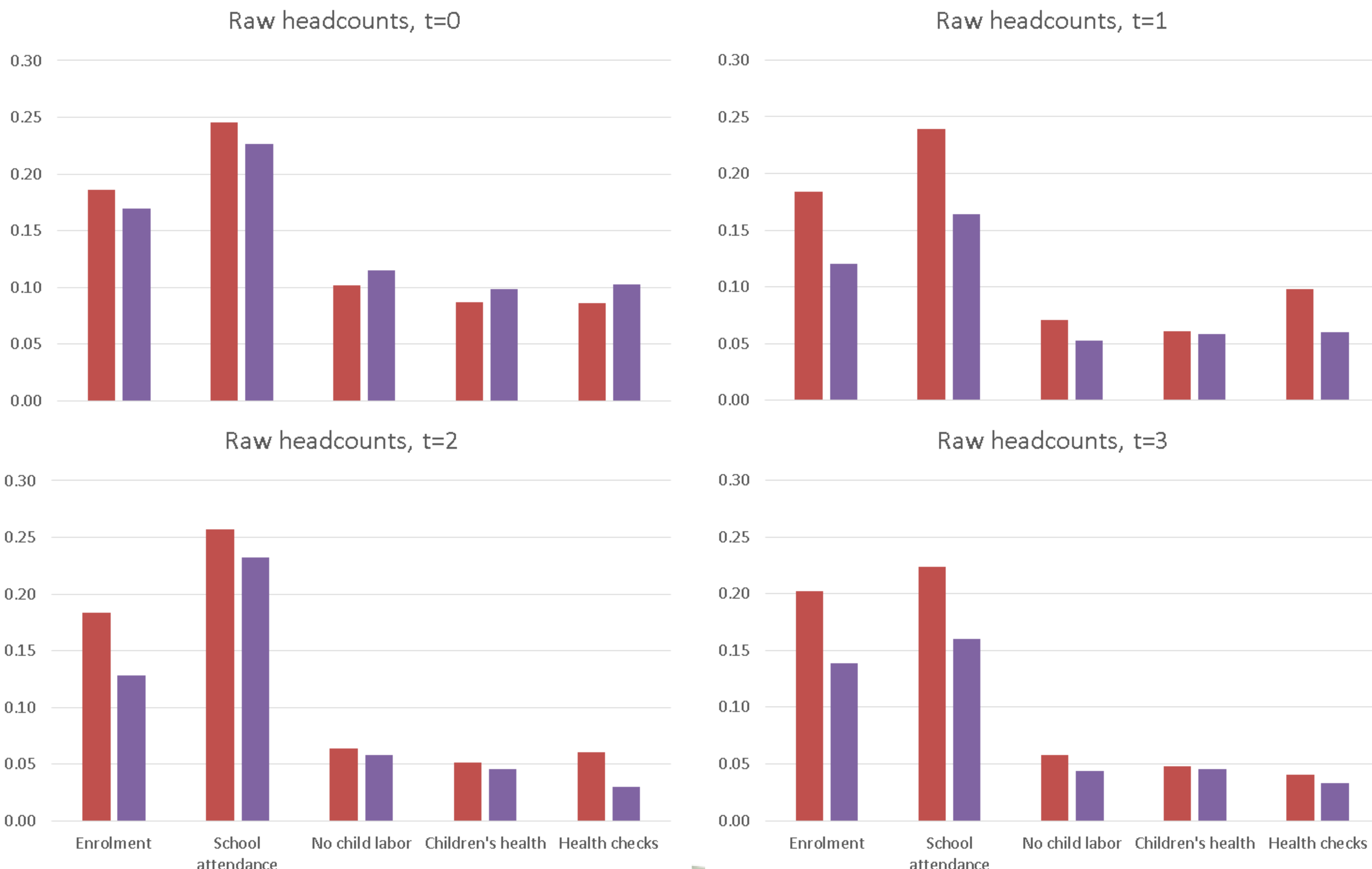


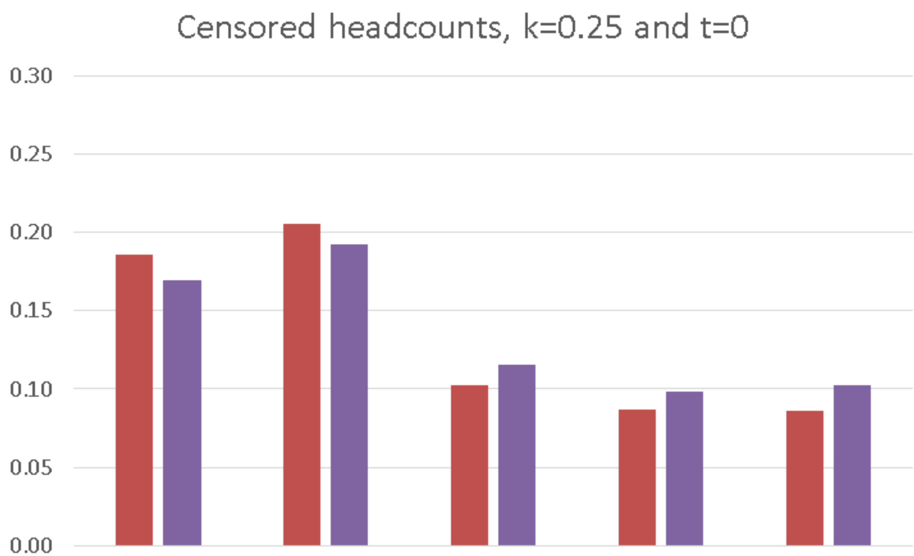
Table: Deprivations count

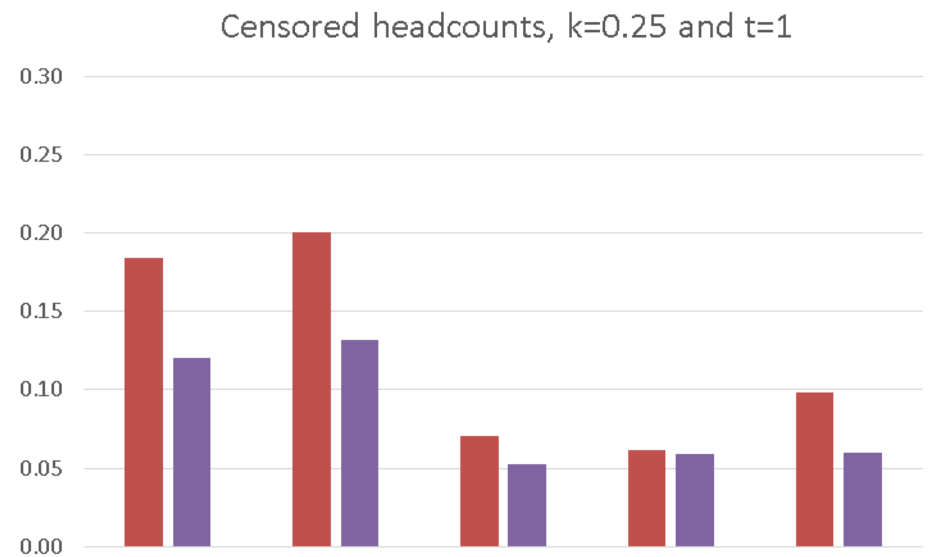
Time	Control			Treated			Diff	Dif-in-Dif
	Value	[95% CI]		Value	[95% CI]			
0	0.122	0.110	0.133	0.128	0.119	0.138	0.007	
1	0.110	0.098	0.121	0.078	0.072	0.084	-0.032***	-0.038***
2	0.098	0.085	0.111	0.078	0.069	0.087	-0.020**	-0.027***
3	0.090	0.081	0.098	0.068	0.062	0.073	-0.022***	-0.029***

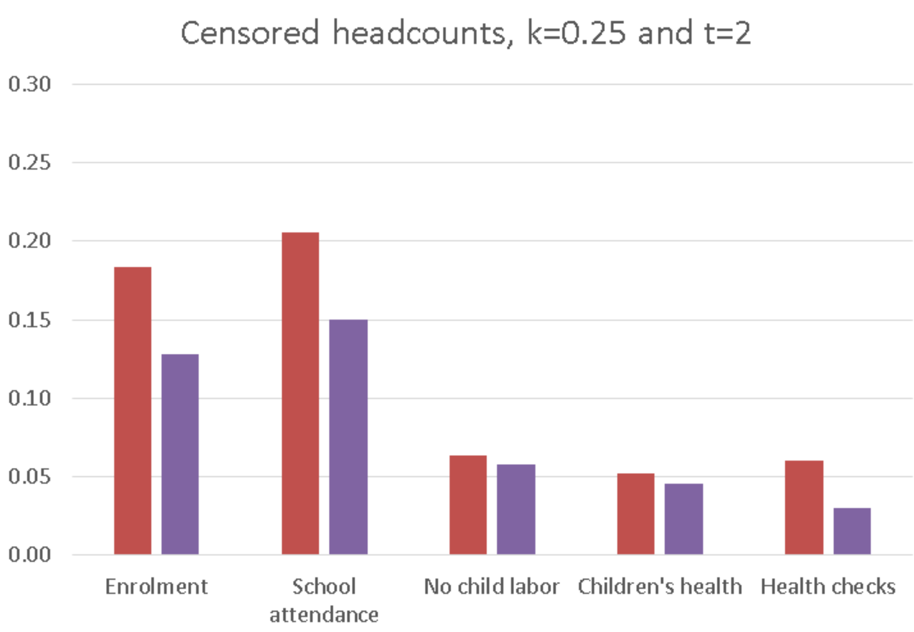
Impact – Raw headcounts

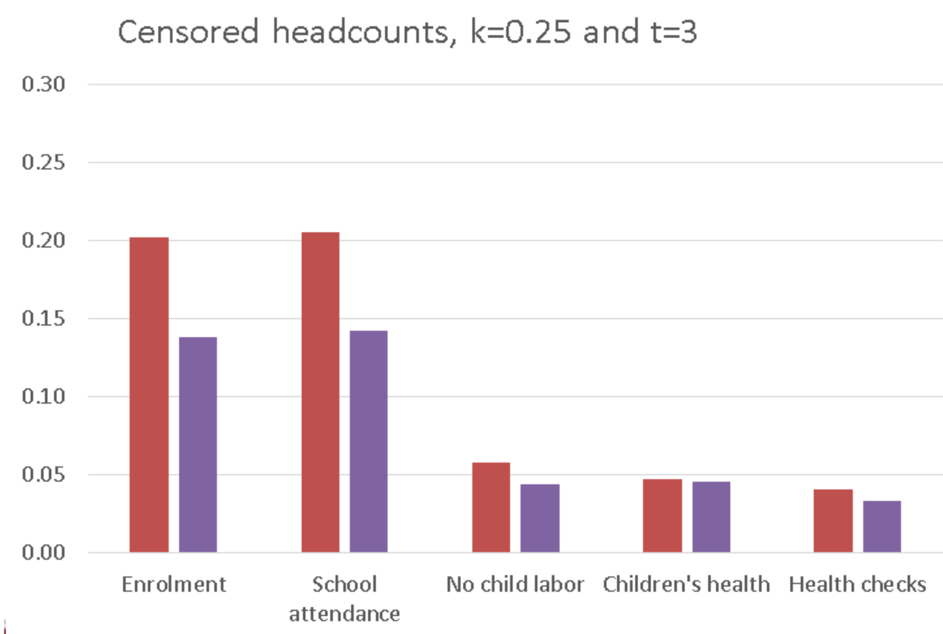


Impact – Censored headcounts









Impact - Probabilities of transition

Table: Probabilities of transition out and into poverty

Probabilities of transition	Cutoff (k)	Periods compared 0-1 Control	0-1 Treated	1-2 Control	1-2 Treated	2-3 Control	2-3 Treated	0-3 Control	0-3 Treated
Out of poverty	0.25	49.0%	63.1%	45.5%	55.8%	46.8%	56.3%	59.9%	69.3%
	0.5	76.9%	83.5%	69.8%	79.3%	74.9%	82.8%	85.8%	88.7%
Into poverty	0.25	22.8%	16.5%	15.9%	14.1%	17.0%	14.9%	21.3%	15.8%
	0.5	6.3%	3.7%	5.2%	2.9%	4.5%	3.3%	5.6%	3.2%

Decomposition

- Only panel data for baseline and period 1
- k= 0.25

Decompositions	Control	Treated
Overall variation in MPI		
Multidimensional Measure (M0) baseline	.111	.116
Multidimensional Measure (M0) after 1 period	.105	.073
Absolute variation	-0.006	-0.043
Relative variation	-5.2%	-36.8%
Decomposition variation in M0 by H and A		
Total % contribution (ΔM0 for Group = 100)	100.0%	100.0%
Incidence of poverty effect (H)	81.3%	89.8%
Intensity of poverty effect (A):	18.7%	10.2%

Decomposition – Indigenous group

- Only panel data for baseline and period 1
- k= 0.25

Decompositions	Non-indigenous	Indigenous	Control	Non-indigenous	Indigenous	Treated
Overall variation in MPI						
Multidimensional Measure (M0) baseline	.128	.087	.111	.128	.100	.116
Multidimensional Measure (M0) after 1 period	.114	.093	.105	.081	.063	.073
Absolute variation	-0.015	0.006	-0.006	-0.047	-0.038	-0.043
Relative variation	-11.3%	6.7%	-5.2%	-36.5%	-37.3%	-36.8%
% shared (based on baseline figures):						
Population	56.9%	43.1%	100.0%	57.9%	42.1%	100.0%
Multidimensional Headcount ratio (H)	63.3%	36.6%	100.0%	63.0%	37.0%	100.0%
Multidimensional Measure (M0)	66.1%	33.9%	100.0%	63.6%	36.4%	100.0%
Decomposition variation in M0 by Group						
% contribution of group to MM1 reduction	143.6%	-43.6%	100.0%	63.0%	37.0%	100.0%
Decomposition variation in M0 by H and A						
Total % contribution (ΔM0 for Group = 100)	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
→ Incidence of poverty effect (H)	86.7%	99.2%	81.3%	91.0%	87.7%	89.8%
→ Intensity of poverty effect (A):	13.3%	0.8%	18.7%	9.0%	12.3%	10.2%

Decomposition – Family structure

- Only panel data for baseline and period 1
- k= 0.25

Decompositions	No children	Only 0-2	Only 6-14	Children 0-2 & 6-14	Treated
Overall variation in MPI					
Multidimensional Measure (M0) baseline	.000	.110	.084	.192	.119
Multidimensional Measure (M0) after 1 period	.018	.050	.067	.094	.071
Absolute variation	0.018	-0.06	-0.02	-0.10	-0.048
Relative variation		-54.6%	-19.6%	-51.1%	-40.3%
% shared (based on baseline figures):					
Population	8.9%	9.2%	44.3%	37.6%	100.0%
Multidimensional Headcount ratio (H)	0.0%	10.2%	34.0%	55.8%	100.0%
Multidimensional Measure (M0)	0.0%	8.4%	31.0%	60.6%	100.0%
Decomposition variation in M0 by Group					
% contribution of group to MM1 reduction	-3.4%	11%	15%	77%	100.0%
Decomposition variation in M0 by H and A					
Total % contribution (ΔM0 for Group = 100)	100.0%	100.0%	100.0%	100.0%	100.0%
Incidence of poverty effect (H)	100.0%	96.7%	96.5%	86.2%	88.5%
Intensity of poverty effect (A):	0.0%	3.3%	3.5%	13.8%	11.5%

Impact – Other analysis

- Estimate the DID including baseline controls
- Decomposition of program's impact by sub-groups:
  - Gender of household head
  - …
- Ranking regions by program's performance
- Impact of program on chronicity of poverty


Tabita, Kenya
Rabiya, India
Stephanie, Madagascar
Agatha, Madagascar
Dalma, Kenya
Ann-Sophia, Kenya
Valérie, Madagascar

Thank you!