

OPHI

OXFORD POVERTY & HUMAN DEVELOPMENT INITIATIVE

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UNIVERSITY OF
OXFORD

Summer School on Multidimensional Poverty Analysis

Oxford Poverty & Human Development Initiative,
(OPHI), University of Oxford

3–15 July 2017

Marrakech, Morocco

Tabita, Kenya



Rabiya, India



Stephanie, Madagascar



Agatha, Madagascar



Dalma, Kenya



Ann-Sasha, Kenya



Valérie, Madagascar



Impact Evaluation

Bilal Malaeb

12 July 2017

Tabita, Kenya



Rabiya, India



Stephanie, Madagascar



Agatha, Madagascar



Dalma, Kenya



Ann-Saphia, Kenya



Valérie, Madagascar



What is impact Evaluation and where did it come from?



Why Multidimensional Impact Evaluation?



Social Protection Scheme



Has there been an improvement?
Was the policy effective?

Why Multidimensional Impact Evaluation?



Education	✓		✓	✓	✓		✓		✓			
Nutrition	✓						✓	✓				
Sanitation		✓			✓		✓					✓

Why Multidimensional Impact Evaluation?

- If we look at each of these at a time, we may conclude that this intervention enhances education, nutrition, and sanitation.
- However, it is also important to evaluate whether each person has benefited from more than one improvement.
- Ideally, a program/policy improves all relevant simultaneously – but this is not guaranteed.
- This is why assessing the impact in a multidimensional way gives valuable information.

Motivation

- More and more poverty reduction programs are adopting multi-dimensional approaches. Examples:
 - Conditional Cash Transfers (Bouillon & Yanez-Pagans, 2011).
 - Millennium Villages Project
 - Graduating the Ultra-Poor
- But often we are also interested in the impact of naturally occurring events, e.g.:
 - Wars and violence
 - Change of constitution, etc.

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.
- And only a couple of papers on multidimensional impact evaluation.
- More research will be produced in early 2018 at OPHI.

Theory of Change in Impact Evaluations

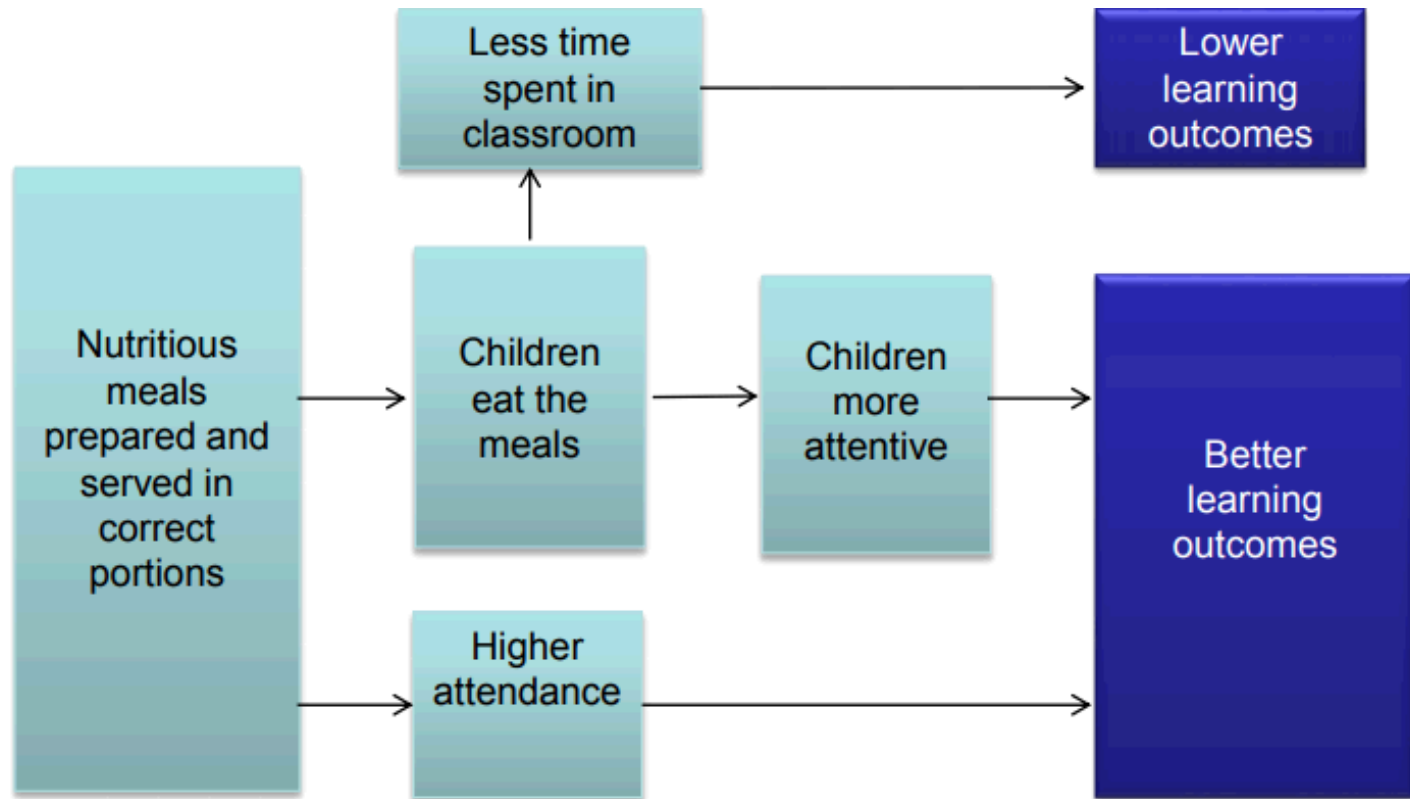
- A theory of change documents the causal links between inputs, activities, outputs and intermediate and final outcomes, and identifies the underlying assumptions.
- Assumptions are what needs to be true for this causal chain to operate.

Howard White (3ie)

Steps in building theory of change

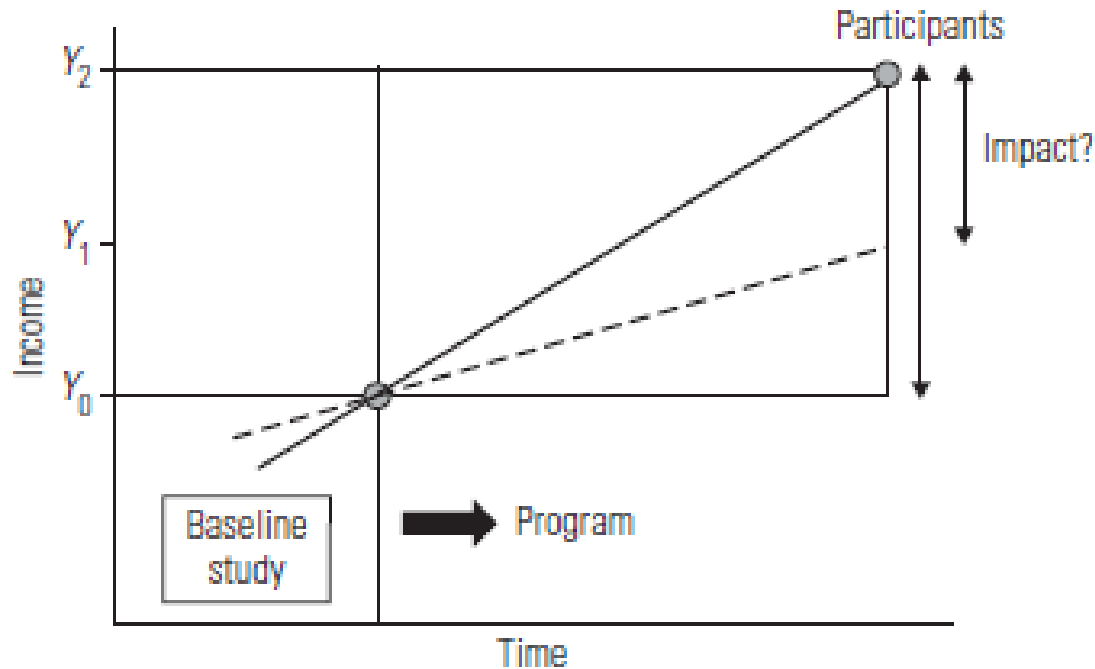
1. Define intervention, objectives and outcomes
2. Lay out main steps in causal chain
3. Identify underlying assumptions
4. Add a temporal dimension
5. Identify key evaluation questions
6. Validate and revise

Intended vs. Unintended Outcomes



Impact Evaluation

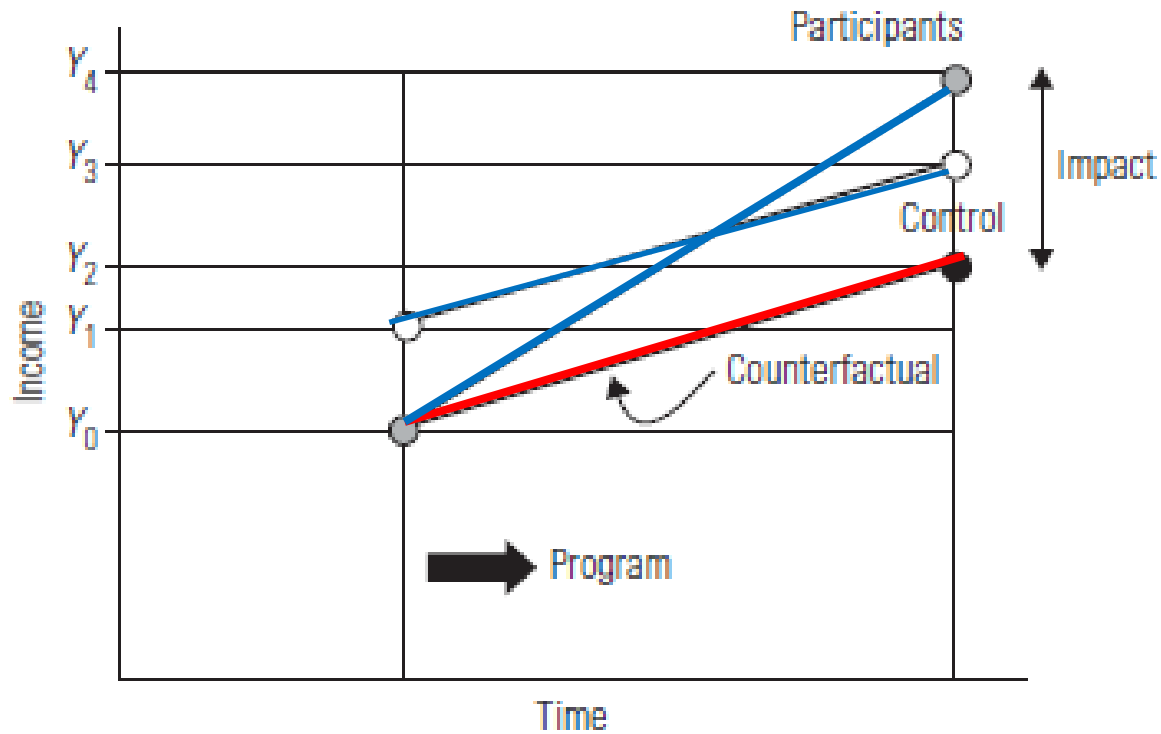
- Before-and-after comparisons



Source: Khandker, Koolwal and Samad (2010)

Impact Evaluation

- With-and-without comparisons



Source: Khandker, Koolwal and Samad (2010)

General Hypothesis

- Hypothesis: In **certain circumstances**, the use of Alkire-Foster multidimensional measures can provide **valuable insights** to the evaluation of social protection programs/policies.
- “**Certain circumstances**”. When program/policy has:
 - A multisectoral approach;
 - Multiple goals;
 - Potential synergies that may trigger effects at different levels.

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;
 - Each objective can be defined in terms of minimum achievement thresholds, \mathbf{z} , for each target unit (person, household, community, etc.);
 - w_d is the weight/importance of objective d ;
 - 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 $\Rightarrow D$ or more indicators
 - z minimum achievement thresholds $\Rightarrow z$ 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:

$$M_0 = H \times A$$

- 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

How to use the AF methodology?

- 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.

Example

Matrices of achievements of treated individuals

	Baseline					Post-treatment				
	Income	Edu	BMI	Sanitation	Water	Income	Edu	BMI	Sanitation	Water
1	85	4	16	0	0	85	5	18	1	1
2	90	6	16	0	0	90	8	18	1	1
3	75	6	17	1	1	75	6	17	1	1
4	50	4	17	1	1	50	4	17	1	1
5	100	4	17	1	1	110	4	17	1	1
6	100	6	17	1	1	110	6	17	1	1
7	100	7	21	1	1	110	7	21	1	1
8	100	8	20.5	1	1	120	8	20.5	1	1
z	100	8	18.5	1	1	100	8	18.5	1	1

Program's average impact in each indicator

Average achievement at baseline	87.50	5.63	17.69	0.75	0.75
Average achievement at post-treatment	93.75	6.00	18.19	1.00	1.00
Program's average impact	6.25	0.38	0.50	0.25	0.25

Example

Deprivation matrices

	Baseline						Post-treatment					
	Income	Edu	BMI	Sanit	Water	No. depriv	Income	Edu	BMI	Sanit	Water	No. depriv
1	1	1	1	1	1	5	1	1	1	0	0	3
2	1	1	1	1	1	5	1	0	1	0	0	2
3	1	1	1	0	0	3	1	1	1	0	0	3
4	1	1	1	0	0	3	1	1	1	0	0	3
5	0	1	1	0	0	2	0	1	1	0	0	2
6	0	1	1	0	0	2	0	1	1	0	0	2
7	0	1	0	0	0	1	0	1	0	0	0	1
8	0	0	0	0	0	0	0	0	0	0	0	0

Program's average impact on raw headcounts

Raw headcount at baseline	0.50	0.88	0.75	0.25	0.25	2.63
Raw headcount at post-treatment	0.50	0.75	0.75	0.00	0.00	2.00
Program's average impact	0.00	-0.13	0.00	-0.25	-0.25	-0.63

Example

Overall goal: no one misses... goals or more					
	k = 1	k = 2	k = 3	k = 4	k = 5
Levels					
Baseline					
Incidence	0.88	0.75	0.50	0.25	0.25
Intensity	0.60	0.67	0.80	1.00	1.00
Adjusted headcount	0.53	0.50	0.40	0.25	0.25
Post-treatment					
Incidence	0.88	0.75	0.38	0.00	0.00
Intensity	0.46	0.50	0.60	0.00	0.00
Adjusted headcount	0.40	0.38	0.23	0.00	0.00
Program's impact					
Incidence (change)	0.00	0.00	-0.13	-0.25	-0.25
Intensity (change)	-0.14	-0.17	-0.20	-1.00	-1.00
Adjusted headcount (change)	-0.13	-0.13	-0.18	-0.25	-0.25

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)

Experimental design

The experimental design used for the evaluation of PROGRESA or Oportunidades takes advantage of the sequential expansion of the program in order to come up with a set of localities that serve the role of controls.

Panel data collected for 24,000 households from 506 localities in the seven states.

Of the 506 localities, 320 localities were assigned to the treatment group ($T = 1$) and 186 localities were assigned as controls ($T = 0$).

Sample

Table 1: Sample size and attrition

Datasets	Sample of eligible households ⁽¹⁾							
	Sample size				Attrition 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'.

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

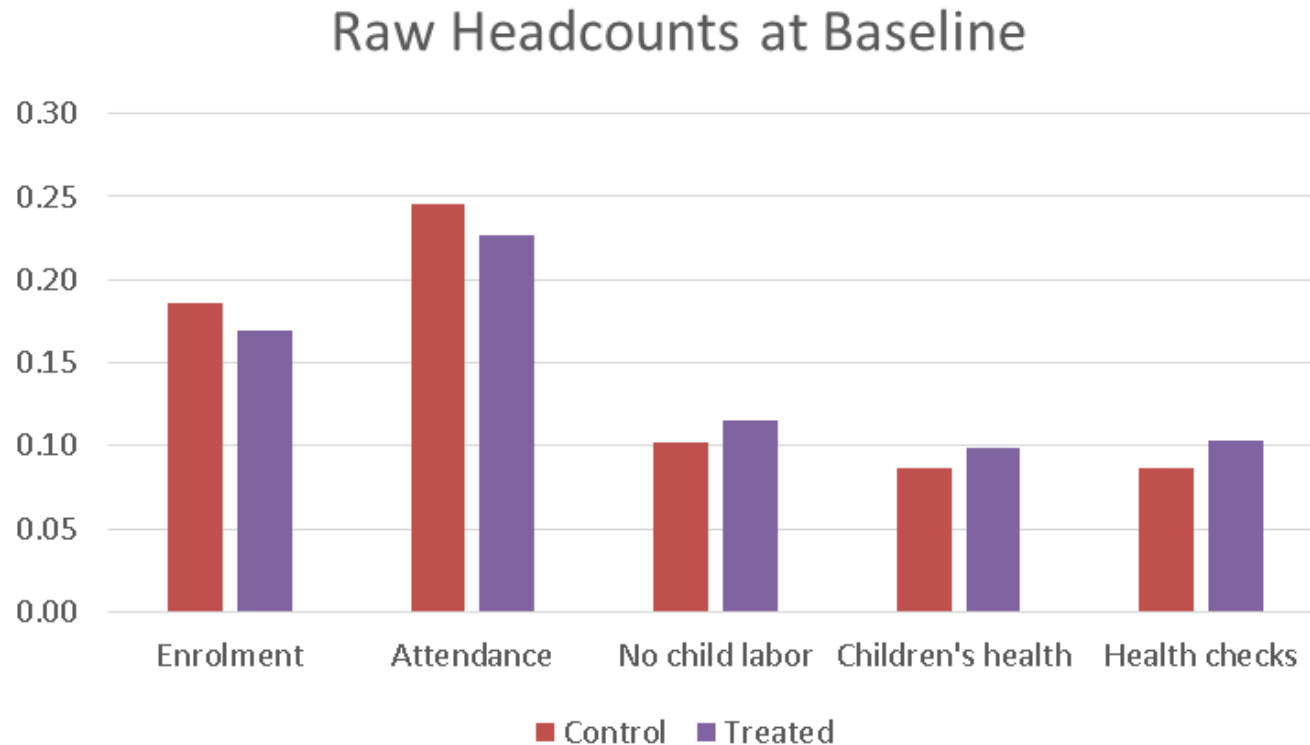
Empirical application

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

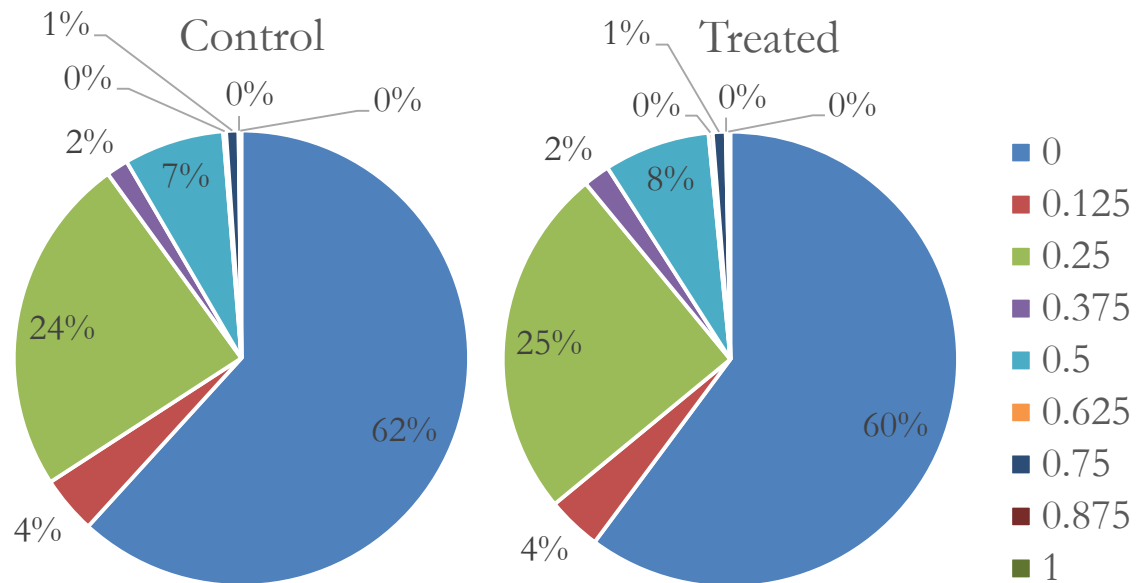
- **Problem:** As all indicators are defined with reference to children, the poverty status of the household is highly dependent on its the demographic structure.

Differences at baseline?



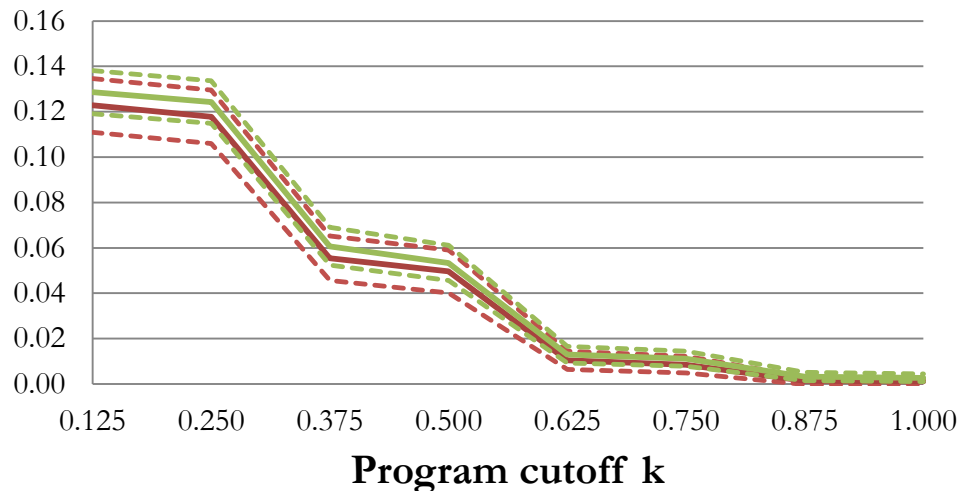
Differences at baseline?

Weighted Deprivation Score at the Baseline

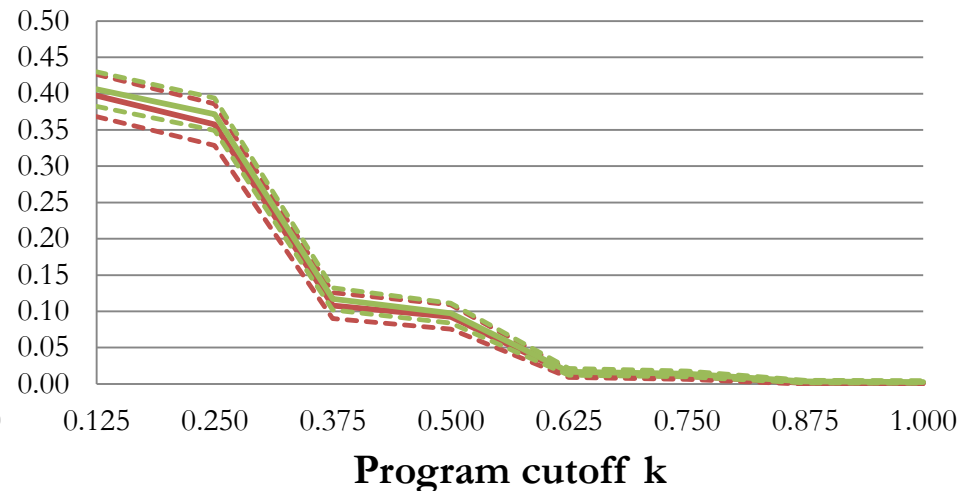


Differences at baseline?

Adjusted Headcount Ratio



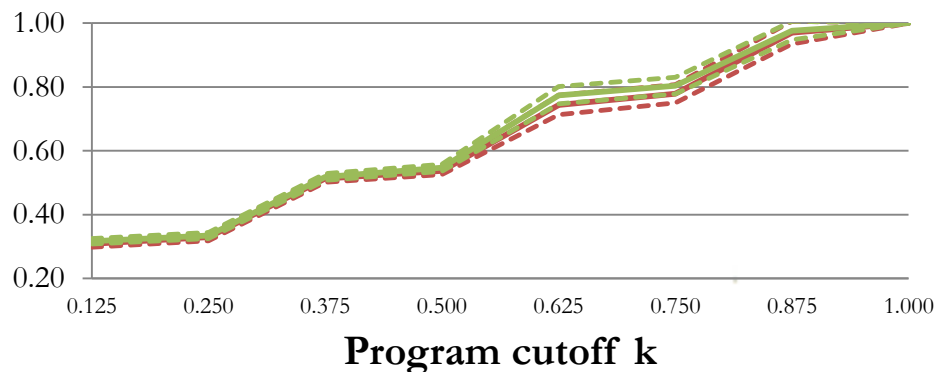
Headcount Ratio



— Control — Treatment

— Control — Treatment

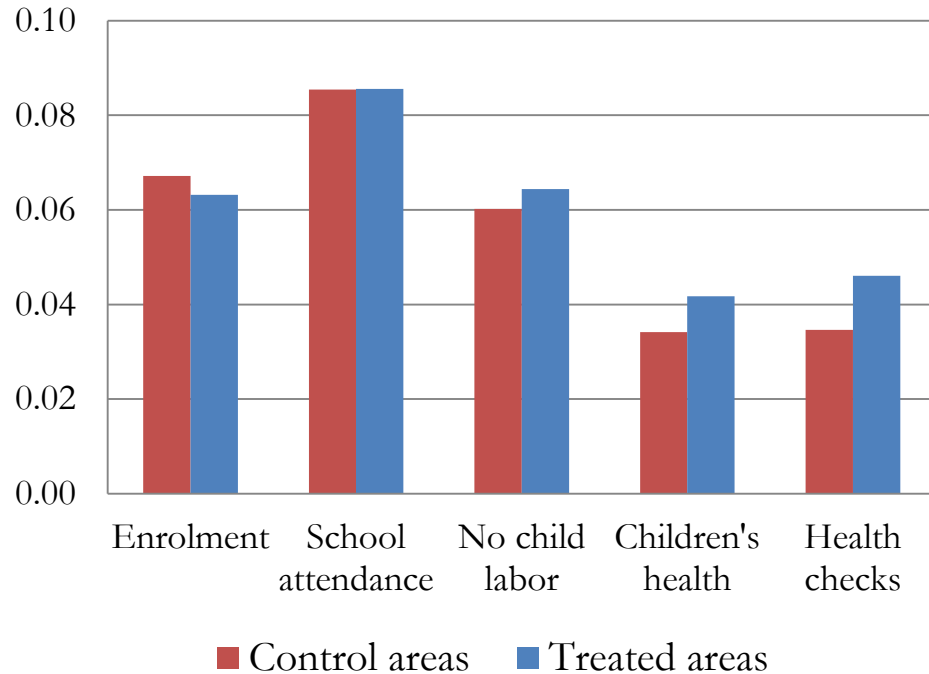
Intensity of poverty



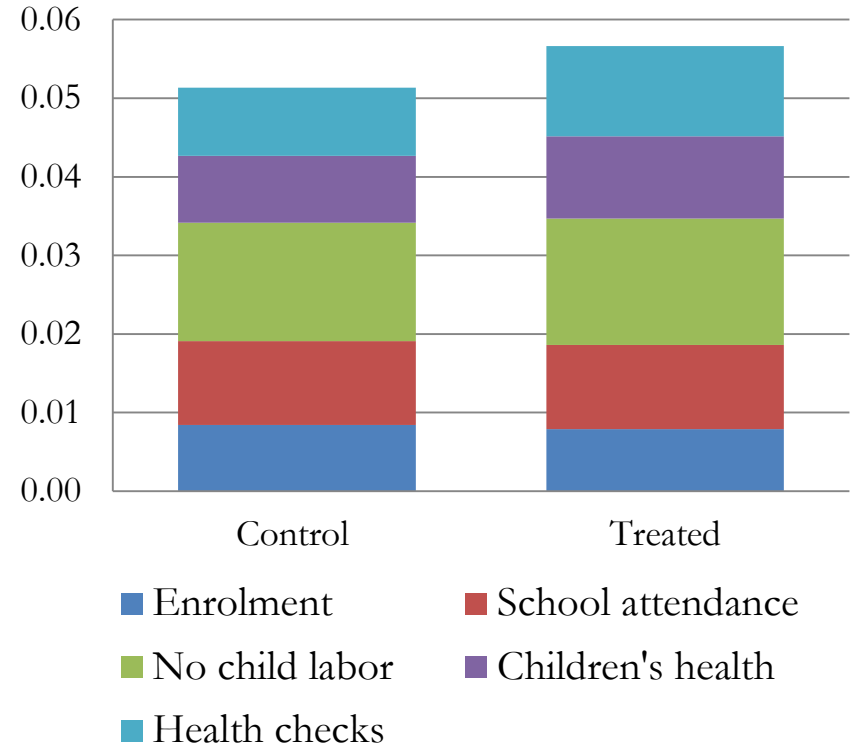
— Control — Treatment

Differences at baseline?

Censored Headcount Ratio, $k=0.375$

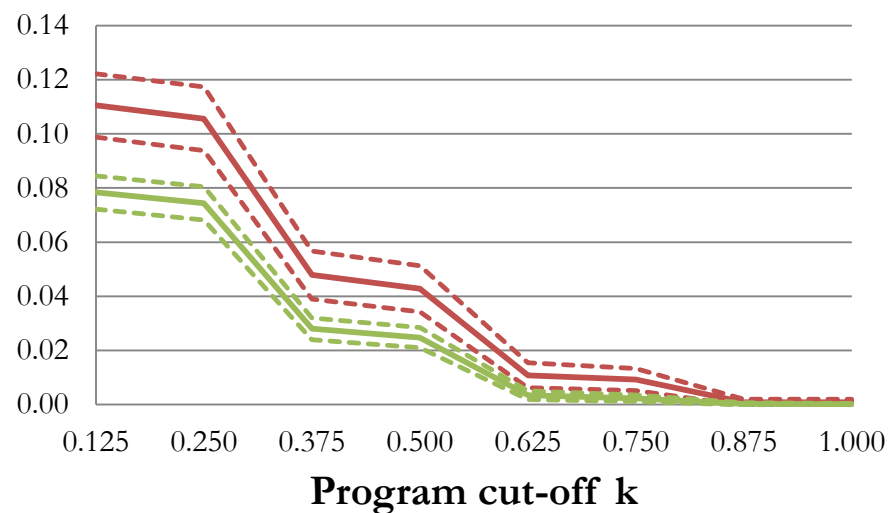


Breakdown of M_0 , $k = 0.375$



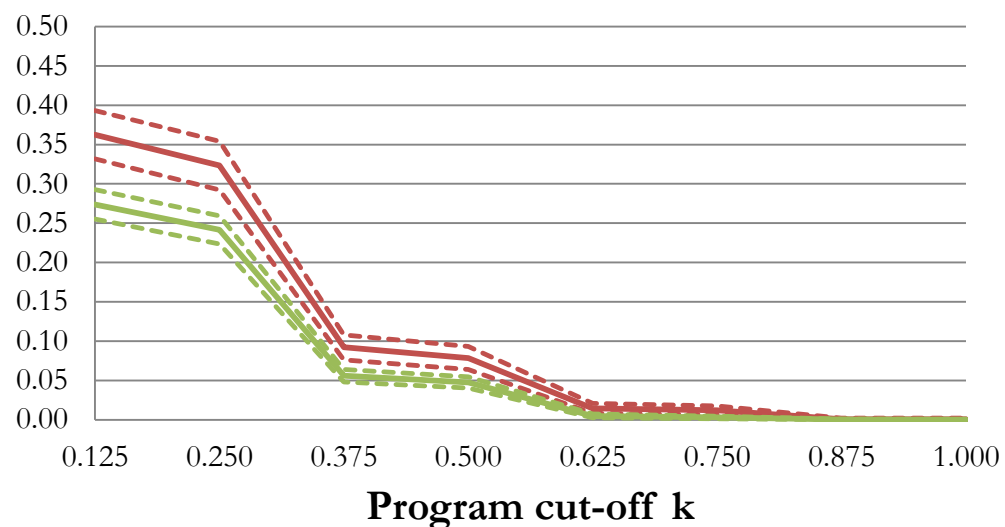
Impact – Using only cross section

Adjusted Headcount Ratio, t=1



— Control — Treatment

Headcount Ratio, t=1

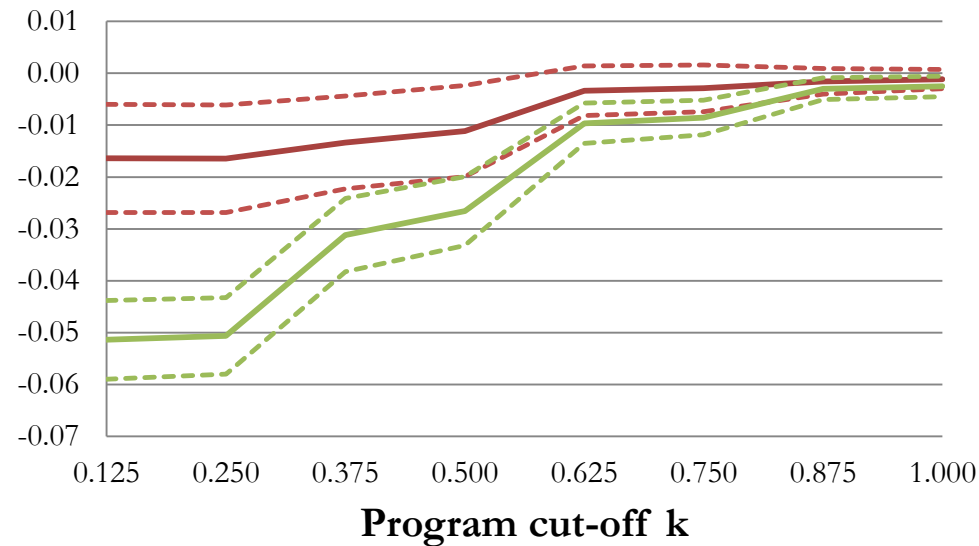


— Control — Treatment

Dashed lines represent confidence intervals

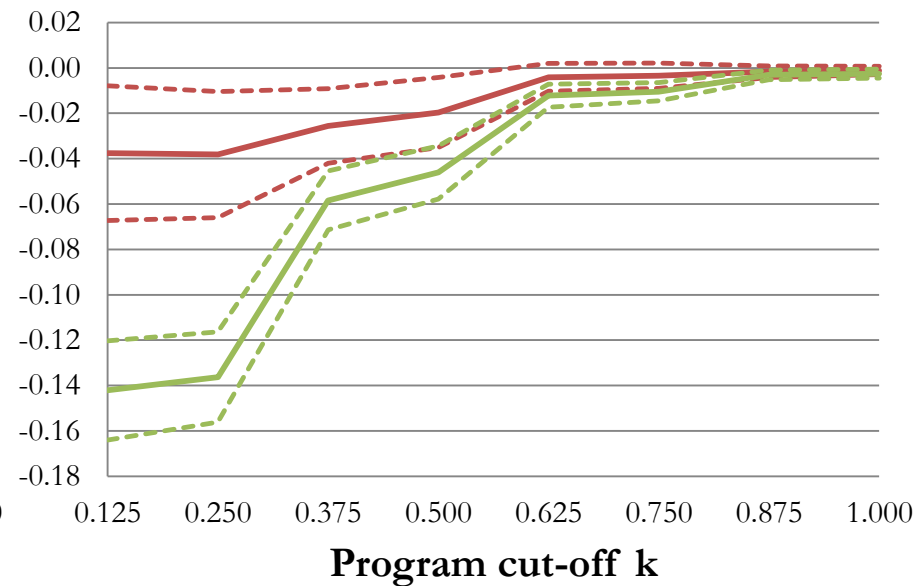
Impact – Using panel data

Change in Adjusted Headcount Ratio, $t = 1$



— Control — Treatment

Change in Headcount Ratio, $t = 1$

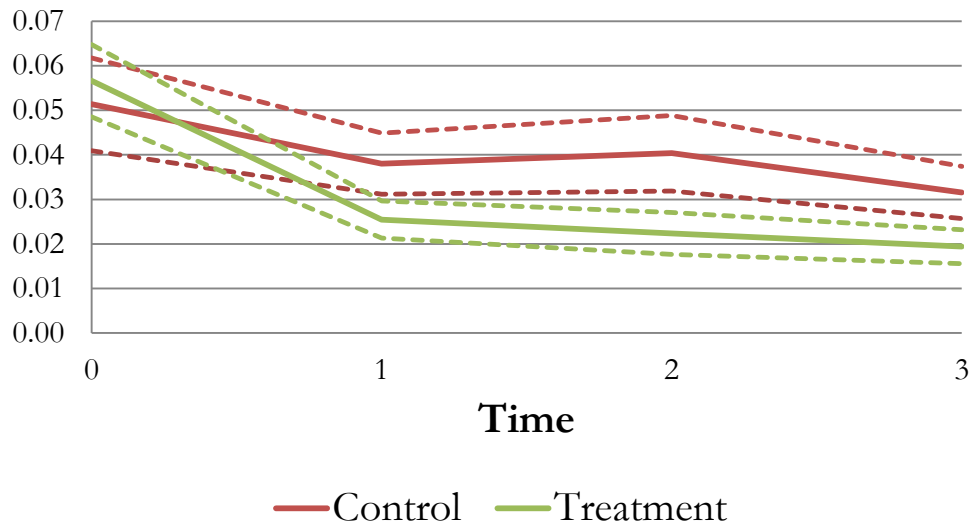


— Control — Treatment

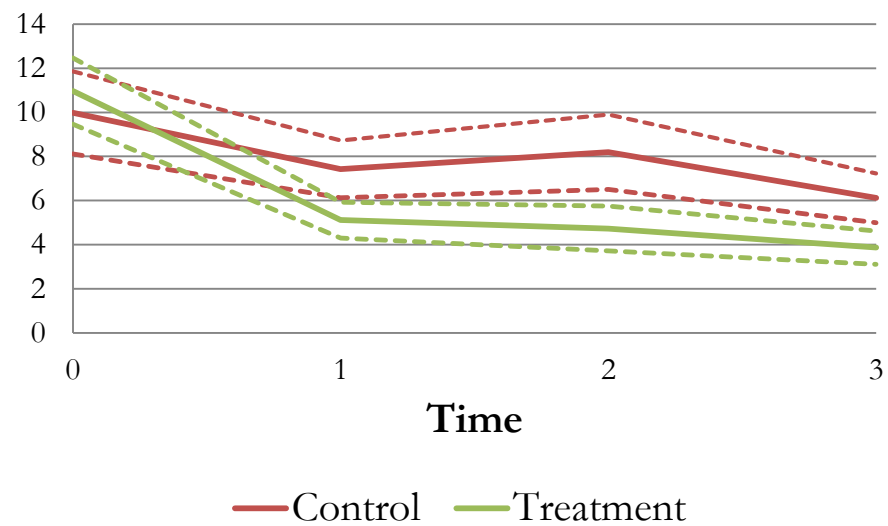
Dashed lines represent confidence intervals

Impact – Using time series

Evolution of Adjusted Headcount Ratio, $k = 0.375$



Evolution of Headcount Ratio, $k = 0.375$



Dashed lines represent confidence intervals

Impact – H and M0

Table: Program's impact considering different cut-offs

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

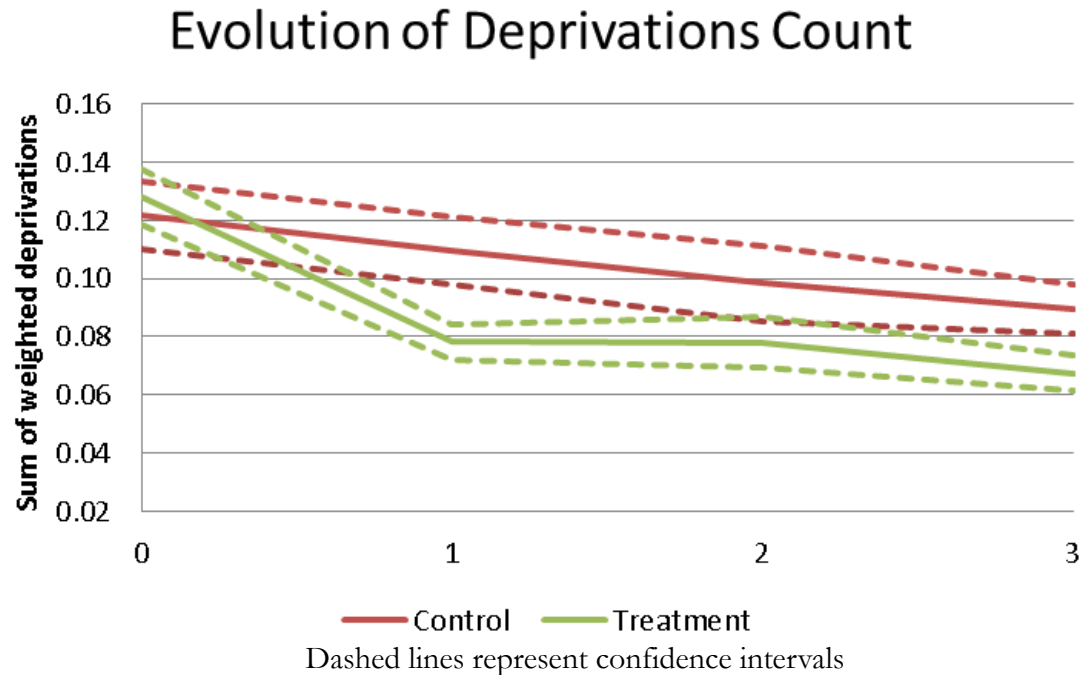
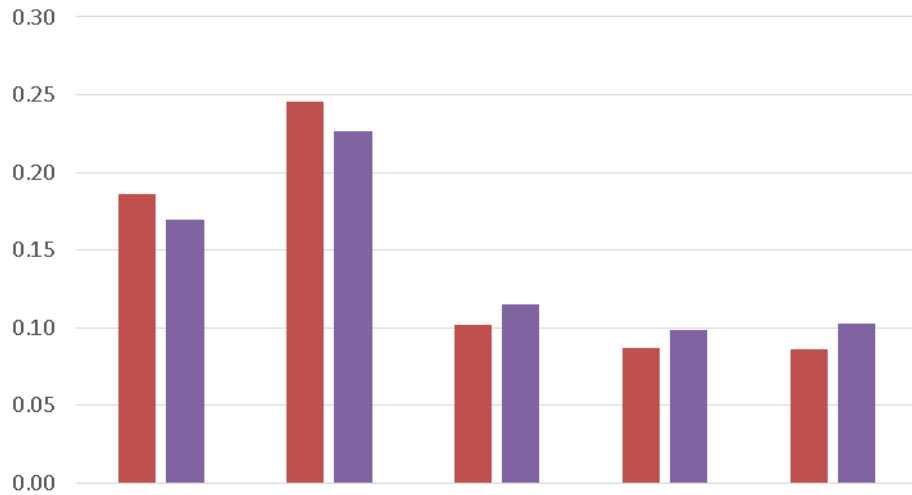


Table: Deprivations count

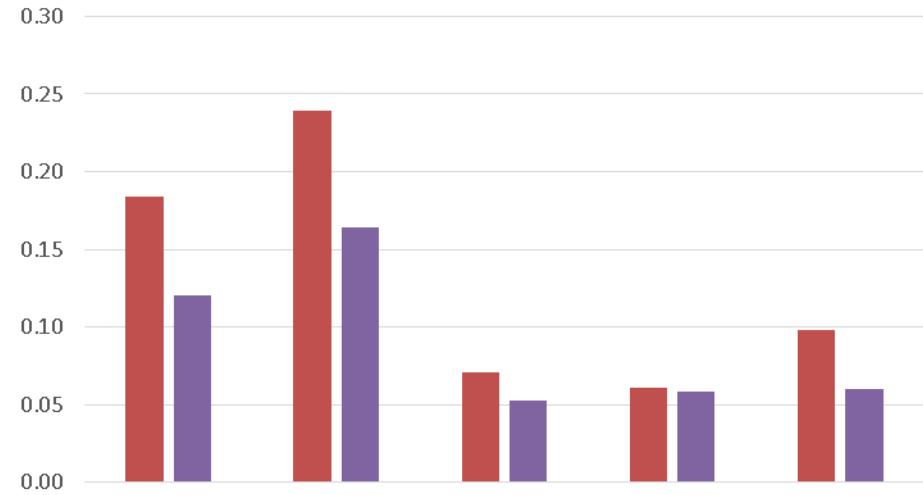
Time	Control			Treated			Diff	Dif-in-Dif
	Value	[95% CI]		Value	[95% CI]			
0	0.122	0.110	0.133	0.128	0.119	0.138	0.007	
1	0.110	0.098	0.121	0.078	0.072	0.084	-0.032***	-0.038***
2	0.098	0.085	0.111	0.078	0.069	0.087	-0.020**	-0.027***
3	0.090	0.081	0.098	0.068	0.062	0.073	-0.022***	-0.029***

Impact – Raw headcounts

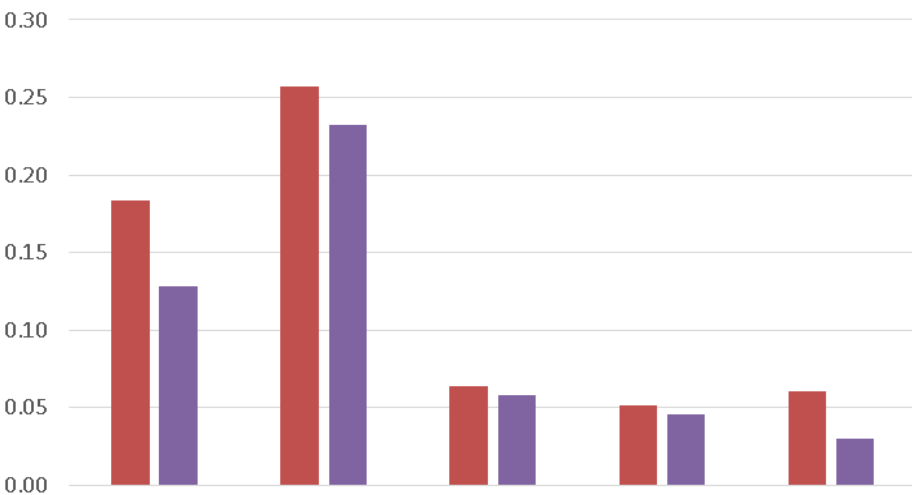
Raw headcounts, t=0



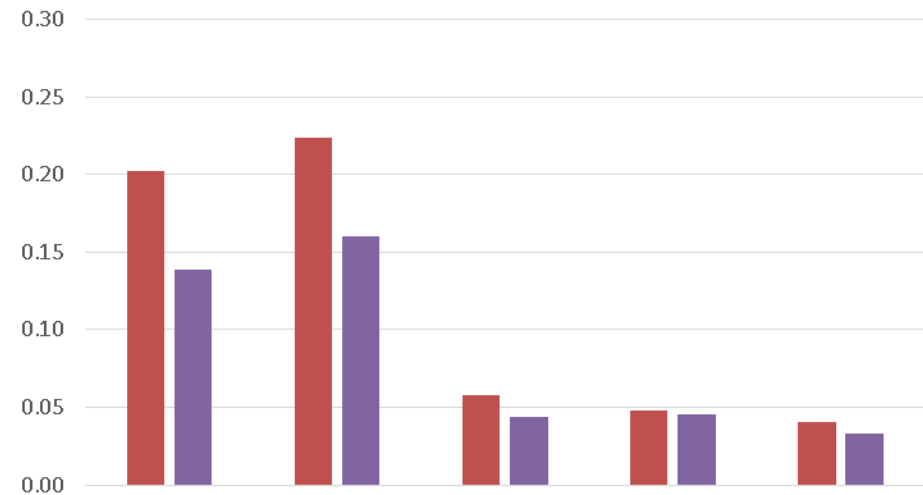
Raw headcounts, t=1



Raw headcounts, t=2

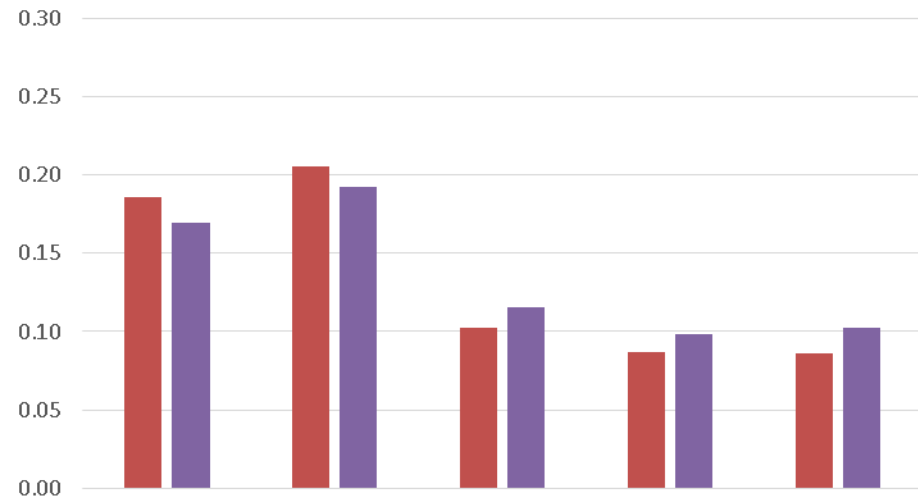


Raw headcounts, t=3

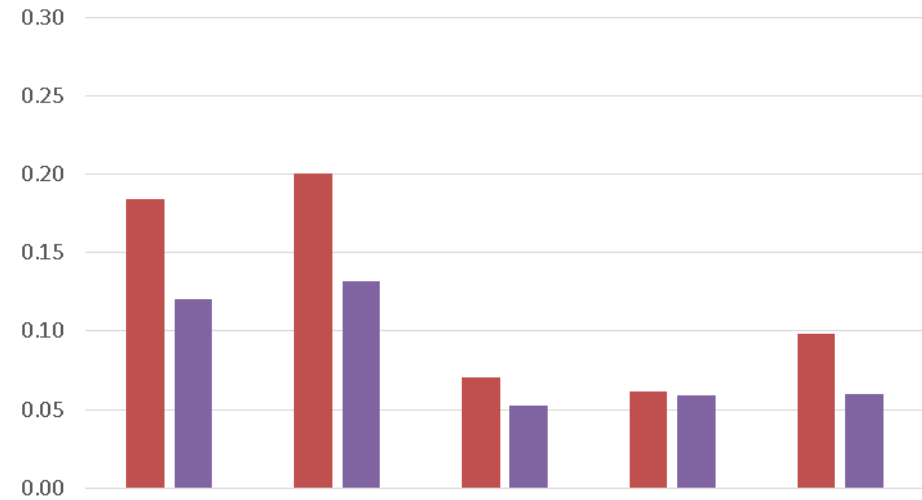


Impact – Censored headcounts

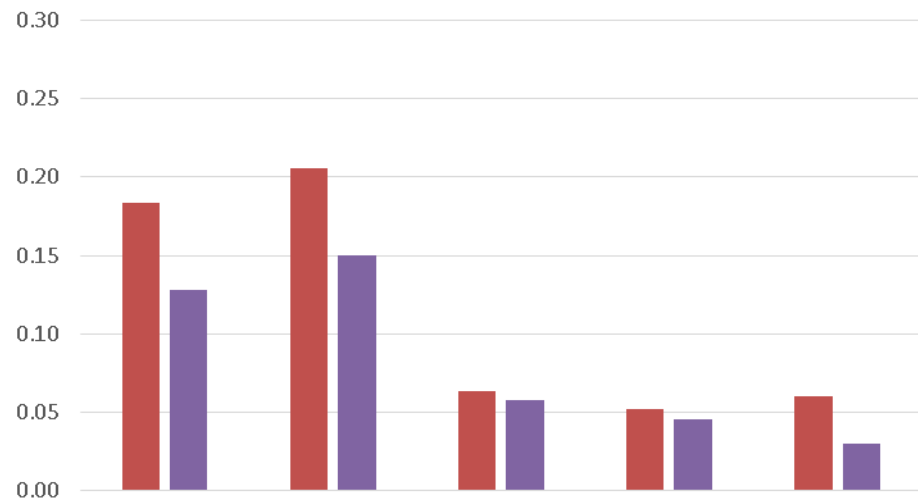
Censored headcounts, $k=0.25$ and $t=0$



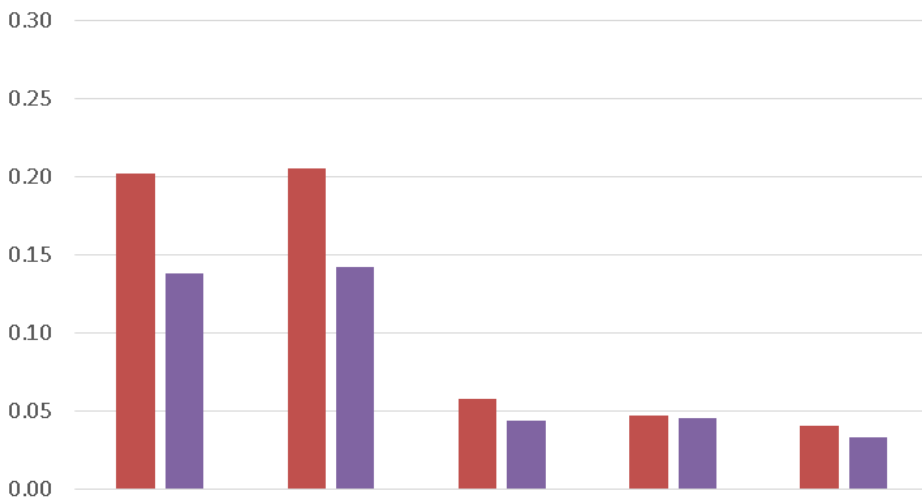
Censored headcounts, $k=0.25$ and $t=1$



Censored headcounts, $k=0.25$ and $t=2$



Censored headcounts, $k=0.25$ and $t=3$



Impact - Probabilities of transition

Table: Probabilities of transition out and into poverty

Probabilities of transition	Cutoff (k)	Periods compared							
		0-1		1-2		2-3		0-3	
		Control	Treated	Control	Treated	Control	Treated	Control	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 ($\Delta M0$ 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 ($\Delta M0$ 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 ($\Delta M0$ 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
 - Other groups
- Ranking regions by program's performance
- Impact of program on chronicity of poverty

Tabita, Kenya

Rabiya, India

Stephanie, Madagascar

Agatha, Madagascar

Dalima, Kenya

Ann-Sophie, Kenya

Valerie, Madagascar



Thank you!