GR 6307 Public Economics and Development

3. Anti-Poverty Programs: Reaching the Poor

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Spring 2022

Motivating Facts

Theory

Evidence from Rich Countries

Targeting in Developing Countries: Who gets the Benefit?

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Targeting in Developing Countries: Who gets the Benefit?

Cohen Dupas & Schaner (AER 2015) *Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial*

Cohen et al (2015): Overview

- ▶ Usually, the targeting tradeoff is that people who know they are ineligible may try to mimic the deserving types in order to gain access to the transfer.
- ► What if incentives are aligned (government and households agree on who should receive the transfer) but households don't know whether they're eligible?
- ► Here: Malaria treatments: artemisinin combination therapies (ACT)
 - ► Huge benefits if have malaria.
 - no direct benefits if don't have malaria, people don't learn real reason they're sick, speeds up development of parasite's resistence.
 - But people who are sick don't know for sure whether they have malaria (or something else) so many people take malaria treatments just in case.
- Experiment in Kenya to test impact of
 - better diagnosis technology
 - subsidies for ACTs

Cohen et al (2015): Setting

- ▶ Malaria causes 200 million illnesses, kills 600K people a year
- Many countries (ncluding Kenya) provide ACTs for free at public health facilities if diagnosed with malaria. But...
 - diagnosis often incorrect
 - stockouts common
 - Have to pay fees, travel far, line up, etc...
- Many households go to private drugstores to get ACTs or other over-the-counter medications (40–97% of the market!)
- ▶ Large subsidies to ACTs to improve access. Subsidy $\sim 95\%$ of cost

Cohen et al (2015): Model

When households receive an illness shock they pick an action

$$a \in \begin{cases} h & \text{seek diagnosis at a formal health facility} \\ s & \text{buy ACTs at a shop} \\ n & \text{buy non-ACT drugs or do nothing} \end{cases}$$

▶ Households who fall ill form a subjective probability that the illnes is malaria with probability π

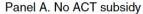
$$V^{a}(\pi) = \pi \left[U_{P}^{a}(\pi) - p_{P}^{a}(\pi) \right] + (1 - \pi) \left[U_{N}^{a}(\pi) - p_{N}^{a}(\pi) \right]$$
$$= \pi V_{P}^{a}(\pi) + (1 - \pi) V_{N}^{a}(\pi)$$

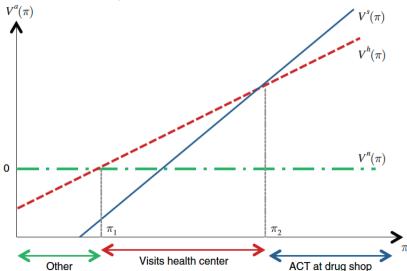
where P denotes malaria-positive, N malaria negative.

- ▶ Assume value of acting increasing with π : $\partial \left(V^a \left(\pi \right) V^n \left(\pi \right) \right) / \partial \pi > 0$ for $a \in \{h, s\}$
- Go to the drug shop iff

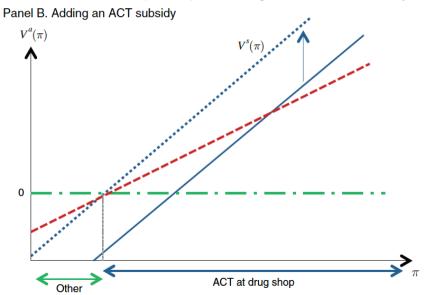
$$V^{s}\left(\pi\right) > \max\left\{V^{h}\left(\pi\right), V^{n}\left(\pi\right)\right\}$$

Cohen et al (2015): Model





Cohen et al (2015): Adding an ACT Subsidy

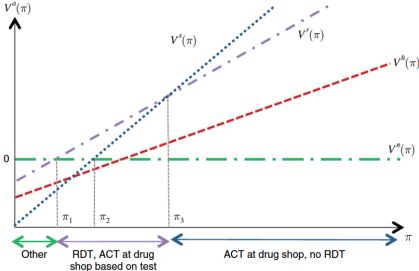


Cohen et al (2015): Model

- Effects of subsidy:
 - More access: More people get ACTs
 - \blacktriangleright Worse targeting: People induced to use ACTs have lower π
 - ▶ Better targeting possible if lots of poor people with high π can't afford ACTs.
- ▶ What about Retail Diagnosis Test (RDT) to improve accuracy of π ?
 - ▶ introduce $V^{r}(\pi)$: Value of taking the RDT and then getting ACT if positive.
 - $ightharpoonup V^{r}\left(\pi
 ight)>V^{s}\left(\pi
 ight)$ at low π since V^{s} relatively more attractive as π increases.

Cohen et al (2015): Effect of RDT

Panel C. Adding an RDT subsidy

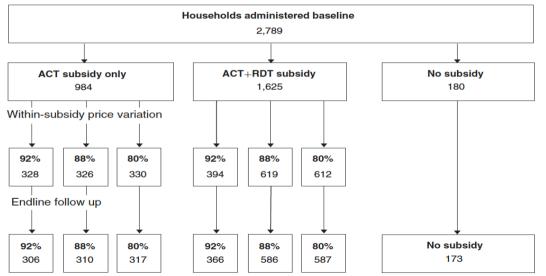


Cohen et al (2015): Experimental Design

- Experiment in Western Kenya in May–December 2009
- ▶ Sample 4 rural drug shops. Sample all households in 4 km catchment radius
- Ecery household interviewed for baseline survey
- ► At the end of the interview, households get 2 ACT vouchers and 2 RDT vouchers if applicable.
- Vouchers redeemable at the local drug shop
- Enumerators explain what RDT is and how it works

Cohen et al (2015): Experimental Design

Catchment area census: target 2,928 households



Cohen et al (2015): Balance

			Dagrassic	on coefficients	and stand	ard arrors	
	Control group	92 percent ACT subsidy	88 percent ACT subsidy	80 percent ACT subsidy	RDT subsidy	Joint test: all subsidies	
	mean (1)	(T1) (2)	(T2) (3)	(T3) (4)	(T4) (5)	= 0 (6)	Observations (7)
Characteristics of inter	viewed hoi	isehold head					
Female	0.867 [0.341]	0.017 (0.029)	0.029 (0.028)	0.040 (0.028)	0.010 (0.012)	1.25 {0.287}	2,789
Age (years)	41.7 [17.3]	-1.98 (1.46)	-3.22** (1.44)	-2.44* (1.45)	0.185 (0.626)	1.61 {0.170}	2,646
Education (years)	5.10 [4.00]	0.141 (0.343)	0.381 (0.341)	0.151 (0.342)	0.169 (0.161)	1.17 {0.323}	2,774
Literate	0.575 [0.496]	0.047 (0.042)	0.050 (0.042)	0.027 (0.042)	0.000 (0.020)	0.621 {0.647}	2,782
Married	0.783 [0.413]	-0.015 (0.035)	0.004 (0.035)	0.006 (0.034)	-0.015 (0.016)	0.514 {0.725}	2,784
Subsistence farmer	0.589 [0.493]	0.052 (0.042)	0.039 (0.042)	0.059 (0.042)	-0.005 (0.019)	0.612 {0.654}	2,787
Number dependents	4.12 [2.78]	-0.263 (0.223)	-0.096 (0.221)	-0.077 (0.222)	0.021 (0.098)	0.809 {0.519}	2,663

Cohen et al (2015): Balance

			Regression coefficients and standard errors						
		Control group mean (1)	92 percent ACT subsidy (T1) (2)	88 percent ACT subsidy (T2) (3)	80 percent ACT subsidy (T3) (4)	RDT subsidy (T4) (5)	Joint test: all subsidies = 0 (6)	Observations (7)	
	Household characteristic	CS							
	Number members	5.48 [2.77]	-0.354 (0.217)	-0.233 (0.214)	-0.197 (0.215)	0.024 (0.092)	0.885 {0.472}	2,789	
	Fraction adults (ages 14+)	0.623 [0.235]	-0.035* (0.020)	-0.048*** (0.019)	-0.024 (0.020)	0.002 (0.009)	2.23* {0.063}	2,337	
	Acres land	2.72 [3.69]	-0.660** (0.330)	-0.601* (0.327)	-0.571* (0.324)	0.197* (0.117)	1.63 {0.164}	2,250	
	Distance from drug shop (km)	1.68 [0.917]	0.012 (0.023)	0.012 (0.022)	0.002 (0.022)	0.010 (0.011)	0.523 {0.719}	2,788	
	Distance from closest clinic (km)	6.57 [2.47]	-0.018 (0.060)	-0.036 (0.059)	-0.043 (0.059)	0.044* (0.027)	0.796 {0.528}	2,785	
	Baseline malaria knowle	edge and i	health practice	rs.					
	Number bednets	1.77 [1.43]	-0.031 (0.120)	-0.060 (0.121)	0.028 (0.120)	0.005 (0.057)	0.476 {0.753}	2,784	
	Share HH members slept under net	0.561 [0.397]	0.023 (0.034)	0.006 (0.034)	0.030 (0.034)	-0.012 (0.017)	0.612 {0.654}	2,661	
The	Only mosquitoes transmit malaria eory Rich Country Evidence	0.517 [0.501] Targeti	0.045 (0.042) ng in Developin	0.011 (0.042) ng Countries	0.024 (0.042) Transfer Design	-0.020 (0.020)	0.842 {0.499}	2,789	

Cohen et al (2015): Balance

Heard of ACTs	0.399 [0.491]	0.016 (0.042)	0.017 (0.041)	0.030 (0.042)	0.001 (0.020)	0.197 {0.940}	2,771
ACT is preferred	0.207	-0.023	-0.029	-0.049	-0.002	0.978	2,771
antimalarial Heard of RDTs	[0.406] 0.128	(0.034) 0.039	(0.034) 0.020	(0.033) 0.021	(0.015) -0.011	{0.418} 0.682	2,786
Treats water	[0.335] 0.408	(0.030) -0.036	(0.029) -0.018	(0.029) 0.004	(0.014) 0.023	{0.604} 1.13	2,779
regularly	[0.493]	(0.041)	(0.041)	(0.041)	(0.019)	{0.339}	
Number of presumed malaria episodes last month	1.20 [1.22]	0.015 (0.102)	-0.008 (0.103)	-0.029 (0.103)	0.033 (0.050)	0.200 {0.939}	2,789
Cost per episode (among	those see	king care)					
Total cost (US \$)	1.63 [1.86]	0.140 (0.293)	-0.040 (0.250)	-0.217 (0.238)	0.131 (0.174)	0.725 {0.575}	1,319
Sample size in treatment	180	328	326	330	1,625		

Notes: The first column shows average values of characteristics for the control group. Columns 2–5 show regression coefficients and standard errors on indicated treatment groups (the omitted category is the control group). All regressions include a full set of strata dummies. Column 6 shows F-statistics and p-values from a test of whether the three ACT subsidy coefficients are jointly equal to zero. Standard deviations are in brackets, standard errors are in parentheses, and p-values are in braces. All tests are based on heteroskedasticity robust standard errors. The exchange rate at the time of the study was around 78 Ksh to US\$1.

Theory Rich Country Evidence Targeting in Developing Countries Transfer Design

Cohen et al (2015): Data

- 3 data sources
- 1. Administrative data from drug shop. Captured by surveyors posted at the 4 shops every single day. Contains 1,700 drug shop visits over 4 months.
 - 1.1 Also administer "surprise ADTs" to random subset of people who redeem ACT voucher (to measure true malarial status)
- 2. Endline survey data from 4 months after vouchers distributed. Includes recall data on all illnesses, where/what treatment sought.
- 3. Symptoms database: 1-year after vouchers, surveyors did unannounced household survey. Ask if anyone is ill and collect all symptoms and administer RDT. Use these to construct "predicted" malaria scores (proxy for π)

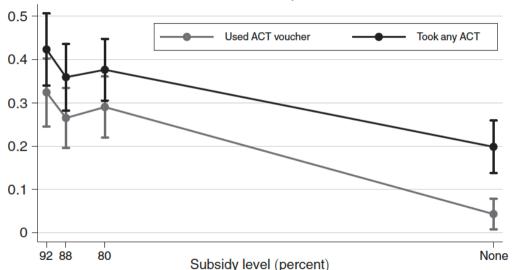
Cohen et al (2015): ACT Acces

$$y_{eh} = \delta + \mathsf{ACTsub}_h' \alpha + \mathbf{x}_h' \gamma + \lambda_{strata} + \varepsilon_{eh}$$

	Took ACT (1)	Took ACT from drug shop (2)	Took ACT from health center (3)	Visited drug shop (4)	Visited health center (5)	Sought no care (6)	Took malaria test (7)	Took antibiotic (8)
Panel A. Pooled impact Any ACT subsidy	0.187*** (0.038)	0.222*** (0.031)	-0.038 (0.030)	0.167*** (0.046)	-0.079* (0.042)	-0.096*** (0.036)	-0.014 (0.038)	-0.072** (0.034)
Panel B. Impact by subs	idy level 0.225***	0.249***	-0.024	0.159***	-0.055	-0.110***	-0.031	-0.046
= 92 percent B2. ACT subsidy = 88 percent	(0.053) 0.161*** (0.050)	(0.046) 0.217*** (0.043)	(0.037) -0.056 (0.037)	(0.058) 0.167*** (0.058)	(0.053) -0.070 (0.052)	(0.042) $-0.097**$ (0.042)	(0.048) -0.042 (0.047)	(0.043) -0.062 (0.040)
B3. ACT subsidy = 80 percent	. ,	0.206*** (0.042)	-0.035 (0.035)	0.173*** (0.054)	-0.106** (0.047)	-0.085* (0.045)	0.023 (0.046)	-0.100*** (0.038)
p-value: B1 = B2 = B3 = 0 p-value: B1 = B2 = B3	0.000*** 0.531	0.000*** 0.723	0.498 0.660	0.004***	0.164 0.535	0.048** 0.846	0.533 0.362	0.066
DV mean (control group)	0.190	0.071	0.119	0.488	0.286	0.226	0.214	0.185
Observations	631	631	631	631	631	631	631	631

Cohen et al (2015): Subsidy Level

Panel A. ACT treatment for first endline illness episodes



Cohen et al (2015): Targeting

$$pos_h = \beta_0 + \beta_1 ACT88_h + \beta_2 ACT80_h + \varepsilon_h$$

TABLE 3—IMPACT OF RETAIL SECTOR ACT SUBSIDY ON ACT TARGETING

	Actual malaria status (1)	Predicted positivity (2)	Predicted positivity (3)
A. ACT subsidy = 88 percent	0.187**	0.112***	0.111**
	(0.081)	(0.042)	(0.053)
B. ACT Subsidy = 80 percent	0.182**	0.107**	0.040
	(0.084)	(0.043)	(0.052)
p-value: $A = B = 0$	0.038**	0.012**	0.104
p-value: $A = B$	0.955	0.906	0.179
DV mean (ACT 92 percent, no RDT)	0.563	0.424	0.422
Observations Data source on Theory Rich Country Evidence Targeting in Developing C	190 Admin. Countries Transfer Design	189 Admin.	178 Endline

Cohen et al (2015): Mechanism

	Used first voucher for patient under 14 (1)	Used first voucher for patient 14 or older (2)
Panel A. Does the ACT subsidy level read	llocate ACTs across dosag	e groups?
A. ACT subsidy = 88 percent	0.035 (0.035)	-0.057** (0.027)
B. ACT subsidy = 80 percent	0.031 (0.034)	$-0.080*** \\ (0.026)$
p-value: $A = B = 0DV mean (ACT 92 percent, no RDT)$	0.540 0.268	0.007*** 0.171
Observations Subsample	984 All households	984 All households

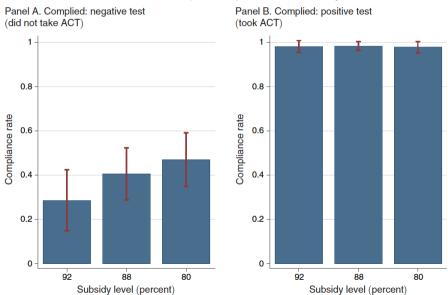
Cohen et al (2015): RDT

	Visited drug shop	Visited health center	Sought no care	Took malaria test	Took RDT test	Took microscopy test	Took ACT	Took antibiotic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Across all ACT	subsidy leve	els						
RDT subsidy	0.004	-0.013	0.010	0.216***		0.017	0.018	0.020
	(0.026)	(0.022)	(0.018)	(0.023)	(0.017)	(0.018)	(0.026)	(0.017)
DV mean (no RDT)	0.657	0.212	0.123	0.207	0.076	0.125	0.389	0.110
Panel B. By ACT subsidy	level							
RDT subsidy × 92%	-0.005	-0.018	0.029	0.258***	0.263***	-0.019	0.002	0.004
ACT subsidy	(0.048)	(0.042)	(0.032)	(0.044)	(0.034)	(0.034)	(0.050)	(0.033)
RDT subsidy × 88%	0.026	-0.045	0.007	0.252***	0.229***	0.000	0.042	-0.016
ACT subsidy	(0.046)	(0.041)	(0.030)	(0.039)	(0.030)	(0.032)	(0.044)	(0.030)
RDT subsidy × 80%	-0.012	0.023	-0.003	0.152***	0.166***	-0.021	0.016	0.070**
ACT subsidy	(0.043)	(0.035)	(0.033)	(0.040)	(0.029)	(0.030)	(0.041)	(0.028)
88% ACT subsidy	-0.006	-0.002	0.014	-0.013	0.004	-0.016	-0.067	-0.011
	(0.058)	(0.052)	(0.038)	(0.048)	(0.032)	(0.041)	(0.058)	(0.038)
80% ACT subsidy	0.009	-0.041	0.020	0.050	0.028	0.007	-0.058	-0.047
	(0.055)	(0.047)	(0.040)	(0.049)	(0.032)	(0.040)	(0.056)	(0.035)
p-value: RDT terms jointly = 0	0.938	0.612	0.832	0.000***	0.000***	0.851	0.787	0.079*
DV mean (ACT 92%, No RDT)	0.667	0.222	0.104	0.194	0.069	0.125	0.444	0.125
Observations	1,993	1,993	1,993	1,993	1,993	1,993	1,993	1,993

Cohen et al (2015): RDT and targeting

		Surprise I that patient is	_	
	Household sought treatment at drug shop (1)	Sample: patients who visited drug shop (2)	Sample: patients who bought subsidized ACT at drug shop (3)	Proportion that redeemed RDT voucher, conditional on seeking treatment at drug shop (4)
Panel A. Across all ACT subsidy levels RDT subsidy	0.025 (0.026)	0.009 (0.039)	0.081** (0.039)	0.818
Panel B. By ACT subsidy level RDT subsidy × 92% ACT subsidy	0.028 (0.045)	0.127* (0.070)	0.163** (0.070)	0.792
RDT subsidy \times 88% ACT subsidy	0.052 (0.044)	-0.058 (0.063)	0.018 (0.062)	0.837
RDT subsidy \times 80% ACT subsidy	-0.010 (0.047)	-0.047 (0.068)	0.061 (0.067)	0.818
DV mean (ACT 92%, no RDT)	0.429	0.556	0.563	_
Observations	1,776	755	687	573

Cohen et al (2015): RDT compliance



Cohen et al (2015): Alternative Subsidy Schemes

		ACT	ACT	ACT	ACT
	No	92 percent	88 percent	80 percent	80 percent +
	subsidy	subsidy	subsidy	subsidy	RDT subsidy
	(1)	(2)	(3)	(4)	(5)
Experimental estimates of access and drug shop	targeting				
Total share taking ACT	0.190	0.415	0.351	0.369	0.385
Share taking ACT at drug shop	0.071	0.320	0.288	0.278	0.303
Share taking ACT at health center	0.119	0.095	0.063	0.084	0.078
Targeting at drug shop	1.000	0.563	0.750	0.745	0.806
Assumptions for estimates of under- and over-tr		0.296	0.296	0.296	0.296
Share of illness episodes that are malaria ^a	0.386	0.386	0.386	0.386	0.386
Targeting at health center (medium) ^b	0.750	0.750	0.750	0.750	0.750
Targeting at health center (high)	1.000	1.000	1.000	1.000	1.000
Targeting at health center (low)	0.650	0.650	0.650	0.650	0.650
Under- and over-treatment: Preferred estimates	(assuming	medium targe	ting at health	center)	
Overall targeting	0.844	0.606	0.750	0.747	0.795
Over-treatment	0.048	0.266	0.143	0.152	0.129
Under-treatment	0.583	0.347	0.317	0.287	0.207
ation Theory Rich Country Evidence Targeting in Develo	ping Countries	Transfer Design	1		

Motivating Facts

Theory

Evidence from Rich Countries

Targeting in Developing Countries: Who gets the Benefit?

Transfer Design: What is the Benefit?
Baird McIntosh & Özler (QJE 2011) Cash or Condition? Evidence from a Cash Transfer Experiment

Baird et al (2011): Overview

- Should cash transfers come with conditions?
 - CCT: Market failures lead to underinvestment in education/health, conditions make transfers easier to "sell" politically
 - ► UCT: Conditions uneffective, and very costly to enforce
- Conditions are common around the world (attend school, attend clinics for checkups, government work) but
 - are they effective at increasing targeted behavior?
 - What other behaviors do they end up distorting?
- Explore these questions in an experiment in Malawi

Baird et al (2011): Setting

- Work in Zomba District in southern Malawi
- ➤ Sample 176 of the 550 Enumeration Areas (EAs) in 3 strata. 29 in Zomba city 119 within 16 km, 28 "far rural".
- ➤ Survey to get census of never-married females aged 13-22. Those in school at baseline (87%) are the target population for the study.
- ► Randomly sample, stratifying by age and stratum, to get 2,907 schoolgirls.

Baird et al (2011): Experiment

T1: CCT arm (46 EAs). 12/2007 & 1/2008. offered parents monthly transfer on condition regularly attend school. Transfer amount to the parent randomly varied, \$4, \$6, \$8, \$10/month, and to the schoolgirl \$1, \$2, \$3, \$4, \$5. Paid school fees.

T2: UCT arm (27 EAs). Identical offers, but no requirement to attend school

Controls: (88 EAs).

Track attendance, other outcomes for 2008, 2009

Baird et al (2011): Attrition

		Dependent variable								
	(1)	(2)	(3)	(4)	(5)	(6)				
				=1 if information	=1 if information found in					
	=1 if surveyed in Round 3	=1 if surveyed in all three Rounds	=1 if took educational tests	found in Round 2 survey	Round 3 school survey	=1 if legible ledger found				
Conditional treatment	0.020 (0.015)	0.021 (0.030)	0.029* (0.016)	0.033 (0.024)	-0.000 (0.027)	0.116* (0.064)				
Unconditional treatment	0.021 (0.019)	0.030 (0.024)	0.035* (0.020)	-0.029 (0.053)	0.014 (0.028)	0.061 (0.077)				
Mean in the control group	0.946	0.893	0.929	0.890	0.935	0.378				
$\begin{aligned} & \text{Number of observations} \\ & \text{Prob} > F(\text{Conditional} = \text{Unconditional}) \end{aligned}$	2,284 0.965	2,284 0.797	2,284 0.801	2,284 0.246	983 0.627	$821 \\ 0.513$				

Baird et al (2011): Enrolment

Panel A: Program impacts on self-reported	d school enrol	lment								
		Dependent variable: =1 if enrolled in school during the relevant term								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
		Year 1: 2008			Year 2: 2009		Year	3: 2010		
	Term 1	Term 2	Term 3	Term 1	Term 2	Term 3	Total terms (6 terms)	Term 1, post- program		
Conditional treatment	0.007	0.019*	0.041**	0.049***	0.056***	0.061***	0.233***	0.005		
Unconditional treatment	(0.011) 0.034*** (0.010)	(0.011) 0.051*** (0.011)	(0.017) 0.054*** (0.018)	(0.017) 0.072*** (0.021)	(0.018) 0.095*** (0.022)	(0.019) 0.101*** (0.021)	(0.070) 0.406*** (0.079)	(0.025) 0.074*** (0.026)		
Mean in the control group	0.958	0.934	0.900	0.831	0.800	0.769	5.191	0.641		
Number of observations	2,087	2,087	2,086	2,087	2,087	2,087	2,086	2,086		
Prob > F(Conditional = Unconditional)	0.006	0.012	0.460	0.299	0.102	0.098	0.038	0.028		
Panel B: Program impacts on teacher-repo	orted school er	rollment								
Conditional treatment	0.043***	0.044***	0.061***	0.094**	0.132***	0.113***	0.535***	0.058*		
	(0.015)	(0.016)	(0.018)	(0.041)	(0.035)	(0.039)	(0.129)	(0.033)		
Unconditional treatment	0.020	0.038**	0.018	0.027	0.059	0.033	0.231*	0.001		
	(0.015)	(0.017)	(0.023)	(0.038)	(0.037)	(0.039)	(0.136)	(0.036)		
Mean in the control group	0.906	0.881	0.852	0.764	0.733	0.704	4.793	0.596		
Number of observations	2,023	2,023	2,023	852	852	852	852	847		
${\bf Prob} > {\it F}({\bf Conditional} = {\bf Unconditional})$	0.173	0.732	0.067	0.076	0.014	0.020	0.011	0.108		

Baird et al (2011): Misreporting

	Dependent variable				
	(1)	(2)			
	Core respondents over-reporting	Teachers over-reporting			
Conditional treatment	-0.093*	-0.021			
	(0.052)	(0.035)			
Unconditional treatment	-0.001	-0.014			
	(0.058)	(0.038)			
Mean in the control group	0.170	0.052			
Number of observations	325	325			
Prob > F(Conditional = Unconditional)	0.02	0.79			

Baird et al (2011): Attendance

	Dependent variable: Fraction of days respondent attended school				
	(1)	$(2) \qquad (3)$		(4)	(5)
	Term 1, 2009	Term 2, 2009	Term 3, 2009	Overall 2009	Term 1, 2010
Conditional treatment	0.139*** (0.045)	0.014 (0.033)	0.169** (0.085)	0.080** (0.035)	0.092** (0.041)
Unconditional treatment	0.063 (0.056)	0.038 (0.033)	0.118 (0.102)	0.058 (0.037)	-0.038 (0.053)
Mean in the control group Number of observations	0.778 284	0.849 285	0.688	0.810 319	0.801 211
Prob > F(Conditional = Unconditional)	0.129	0.334	0.358	0.436	0.010

Baird et al (2011): Attainment

	Dependent variable				
	(1)	(2)	(3)	(4)	
	English test score (standardized)	TIMMS math score (standardized)	Non-TIMMS math score (standardized)	Cognitive test score (standardized)	
Conditional treatment	0.140***	0.120*	0.086	0.174***	
Unconditional treatment	(0.054) -0.030 (0.084)	(0.067) 0.006 (0.098)	(0.057) 0.063 (0.087)	(0.048) 0.136 (0.119)	
Number of observations $Prob > F(Conditional =$	2,057	2,057	2,057	2,057	
Unconditional)	0.069	0.276	0.797	0.756	

Baird et al (2011): Marriage & Pregnancy

	Dependent variable				
	(1)	(2)	(3)	(4)	
	=1 if ever married		=1 if ever pregnant		
	Round 2	Round 3	Round 2	Round 3	
Conditional treatment	0.007	-0.012	0.013	0.029	
	(0.012)	(0.024)	(0.014)	(0.027)	
Unconditional treatment	-0.026**	-0.079***	-0.009	-0.067***	
	(0.012)	(0.022)	(0.017)	(0.024)	
Mean in the control group	0.043	0.180	0.089	0.247	
Number of observations Prob > F(Conditional =	2,087	2,084	2,086	2,087	

0.265

0.003

Baird et al (2011): Decomposition

- ▶ How to rationalize these results? Imagine 3 strata of schoolgirls:
- 1. UCT Compliers: UCT is sufficient to keep them in school. Differences in program impact must be due to intensive margin responses to conditionality
- 2. CCT Compliers: Enrolled under CCT but not UCT. Conditionality lowers opportunity cost of schooling.
- 3. Noncompliers: Never enrol. Only receive transfers under UCT.
- Overall effects depend on sizes of the three strata and effects in each group.

Baird et al (2011): Strata Sizes

	(1)	(2)	(3)
	Enrolled	${\bf Not\ enrolled}$	Total
Control, %	1.7	46.9	19.9
(row %)	(59.8)	(40.2)	(100.0)
Conditional treatment, %	0.5	50.8	16.0
(row %)	(69.2)	(30.8)	(100.0)
Unconditional treatment, %	0.3	25.2	10.1
(row %)	(60.5)	(39.5)	(100.0)
Total, %	1.1	44.2	17.2
(row %)	(62.7)	(37.3)	(100.0)

Baird et al (2011): Enrolment and Marriage

	Dependent variable				
	(1)	(2)	(3)	(4)	
	=1 if enrolled term 1 2010	=1 if ever married	=1 if ever married	=1 if ever married	
	All	All	Enrolled	Not enrolled	
Conditional treatment	0.058*	-0.026	-0.012	0.033	
	(0.034)	(0.037)	(0.015)	(0.097)	
Unconditional treatment	-0.000	-0.088***	-0.011	-0.159**	
	(0.036)	(0.030)	(0.010)	(0.067)	
Mean in the control group	0.598	0.199	0.017	0.469	
Sample size	844	844	490	354	
Prob > F(Conditional =					
Unconditional)	0.099	0.106	0.857	0.088	

Baird et al (2011): Age Heterogeneity

	Dependent variable				
	(1)	(2)	(3)	(4)	
	Total number	Standardized			
	of terms enrolled	English test	=1 if ever	=1 if ever	
	(school survey)	score	married	pregnant	
Conditional treatment	0.467***	0.141*	-0.023	-0.008	
	(0.159)	(0.073)	(0.017)	(0.028)	
Unconditional treatment	0.257	-0.116	-0.051**	-0.059***	
	(0.157)	(0.102)	(0.020)	(0.020)	
=1 if Over 15	-0.786***	-0.546***	0.122***	0.176***	
	(0.244)	(0.058)	(0.026)	(0.027)	
Conditional treatment * Over 15	0.290	0.017	0.037	0.104*	
	(0.291)	(0.089)	(0.056)	(0.054)	
Unconditional treatment * Over 15	0.103	0.245**	-0.067	-0.032	
	(0.255)	(0.110)	(0.042)	(0.046)	
Number of unique observations	852	2,057	2,084	2,087	
Prob > F(Conditional =					
Unconditional)	0.095	0.031	0.188	0.067	
Prob > F(Conditional *)					
Older = Unconditional * Older)	0.364	0.059	0.097	0.027	

Baird et al (20110: Transfer Amount Elasticities

	Dependent variable				
	(1)	(2)	(3)	(4)	
	Total number of terms enrolled (school survey)	Standardized English test score	=1 if ever married	=1 if ever	
Conditional treatment, individual amount	0.024 (0.051)	-0.032 (0.029)	-0.002 (0.008)	0.006 (0.012)	
Unconditional treatment, individual amount	-0.048 (0.064)	-0.019 (0.038)	-0.016 (0.011)	0.013 (0.013)	
Conditional treatment, household amount	-0.027	-0.000	0.001	0.005	
Unconditional treatment, household amount	(0.035) 0.081***	$(0.016) \\ -0.058**$	(0.007) $-0.017**$	(0.010) -0.002	
Conditional treatment, minimum transfer amounts	(0.031) 0.572***	(0.029) 0.202*	(0.007) -0.011	(0.009) 0.001	
Unconditional treatment, minimum transfer amounts	(0.213) 0.094	(0.118) 0.175	(0.044) 0.001	(0.052) -0.089*	
Number of unique observations	(0.167)	2,057	2,084	2,087	
Prob $> F$ (Conditional = Unconditional), individual amount	0.390	0.788	0.300	0.702	
Prob > F(Conditional = Unconditional), household amount Prob > F(Conditional = Unconditional), minimum amount	0.025 0.046	0.082 0.877	0.069 0.834	0.614 0.203	