14.771: Public Finance Lecture

Ben Olken

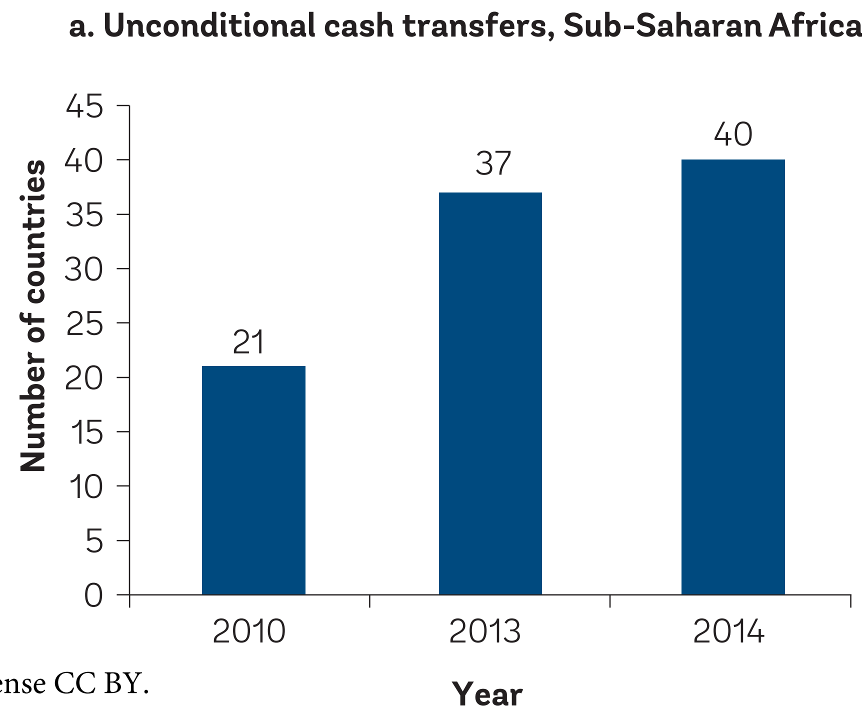
Outline

- From our perspective in rich countries, we sometimes think of poverty and development as going together - i.e., most people in developing countries are 'poor'
- But this masks substantial inequality *within* poor countries
    - For example, in in Indonesia (where I happen to have the data microdata handy), 10th percentile household consumes about US$1 / day per / capita
    - But the 90th percentile household consumes about US$5 / day / capita
    - And this is a very equal country, compared to others in e.g., Latin America
- This creates substantial scope for redistribution within developing countries
- As countries develop a bit of tax capacity, developing country governments are doing this...
- And given the scope of governments, these programs vastly swamp any private sector or NGO-led anti-poverty programs

Spread of redistribution programs

From World Bank (2015): "The State of Social Safety Nets"

Figure 1.2 Social safety net programs have been rising steadily



Spread of redistribution programs

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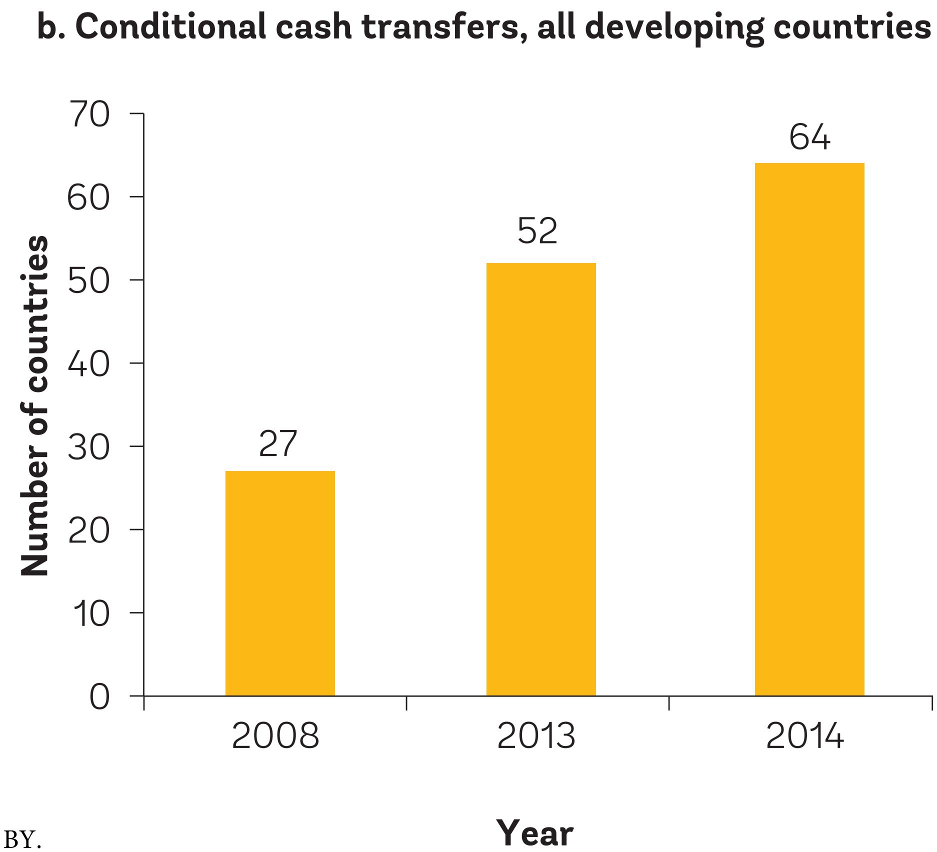


These programs are ubiquitous

From World Bank (2015): "The State of Social Safety Nets"

Table 1.1 Number of Countries with at Least One Type of Social Safety Net Program, by Region

Number of countries

	Region						
Program type	Africa	East Asia and Pacific	Europe and Central Asia	Latin America and the Caribbean	Middle East and North Africa	South Asia	Total of countries with at least one program
Conditional cash transfers	18	7	7	22	5	4	63
Unconditional cash transfers	41	11	29	28	14	7	130
Unconditional in-kind transfers	42	7	8	24	7	4	92
School feeding	45	12	23	28	16	7	131
Public works	39	9	17	17	7	5	94
Fee waivers	12	7	14	10	3	3	49
Total number of countries in respective region	48	21	30	29	19	8	157

And cover hundreds of millions, if not billions, of people

From World Bank (2015): "The State of Social Safety Nets"

Table 1.3 Top Five Social Safety Net Programs, by Scale

Conditional cash transf rs		
Country	**Program nam**	**B n ficiari s (millions)**
Brazil	Bolsa Familia	49
Mexico	Prospera	26
Philippines	Pantawid	19
Colombia	Familias en Acción	12
Bangladesh	Stipend for primary students	8

Unconditional cash transf rs		
Country	**Program nam**	**B n ficiari s (millions)**
	Bantuan Langsung Sementara Masyrakat (BLSM)	61
	BR1M	15

Unconditional in-kind/near-cash transf rs		
Country	**Program nam**	**B n ficiari s (millions)**
Turkey	Gida Yardimi	9
Mexico	Milk grant benefit	6
China	Wubao	6
Sudan	General food distribution program	5
Ghana	Free uniforms/books	5

And cover hundreds of millions, if not billions, of people

From World Bank (2015): "The State of Social Safety Nets"

Table 1.3 Top Five Social Safety Net Programs, by Scale
(Continued)

School feedin		
Country	**Pro ram name**	**Beneficiaries (millions)**
	Program de Alimentacao Escolar	47
	School feeding	9

Public works pro rams		
Country	**Pro ram name**	**Beneficiaries (millions)**
	PSNP[a]	7
	Regional public works	2

Fee waivers		
Country	**Pro ram name**	**Beneficiaries (millions)**
Indonesia	Jamkesmas, including Jampersal	86
China	Medical assistance	42
Philippines	PhilHealth	39
Turkey	Green card	36
Ukraine	Housing and utility allowances	5

Questions about redistribution programs

- How should beneficiaries be selected? Should programs be universal, or targeted so only the poor could be eligible?
  - Aside: how could a universal program achieve redistribution?
- Conditional on doing a particular type of program, what form should it take?

Universal vs. targeted programs

- Basic problem: lack of information about who is really poor.
- This is a problem everywhere.
  - In the US literature, the problem is typically framed that we observe income, not true earning ability.
  - Optimal taxes are set taking into account this asymmetric information (Mirrlees 1971, Saez 2001).
  - If we know more characteristics about individuals that predict poverty (e.g., widowhood), we can "tag" these individuals and assign them different tax schedules (Ackerlof 1978).
- The problem is particularly severe in developing countries: we don't even observe income!
- Three approaches to solving this problem:
  - Subsidies of particular goods (e.g., food subsidies)
  - Universal Basic Incomes (e.g., untargeted cash transfers)
  - Try to do targeted transfers anyway

Poverty metrics

- Standard decomposable metric developed by Foster, Greer, and Thorbecke (1984):
  - Define z as the poverty line.
  - Then for $\alpha \geq 0$ define

$$P_\alpha = \int_0^z \left(\frac{z-y}{z} \right)^\alpha f(y)\, dy$$

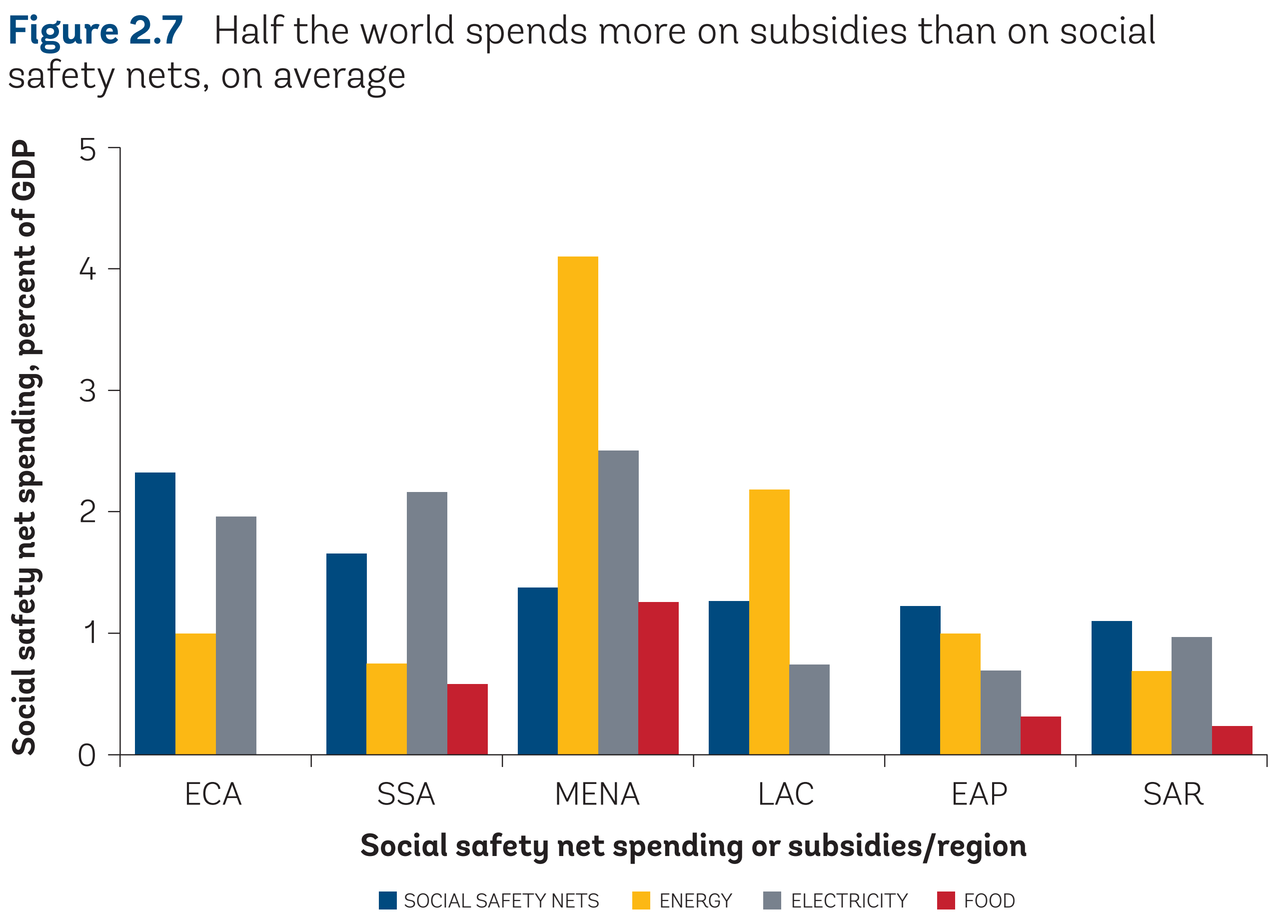
- Special cases:
  - $P_0 = \int_0^z f(y)\, dy$ is the "headcount" ratio, i.e., number of poor people
  - $P_1 = \int_0^z \left(\frac{z-y}{z} \right) f(y)\, dy$ is the "poverty gap",i.e., the amount of money required to bring all poor people up to the poverty line.
  - $\alpha > 1$ puts more weight on the poverty of very poor.
- Key property is decomposability. Assume i subgroups with population shares λ_i. Then

$$P_\alpha = \sum_i \lambda_i P_{i,\alpha}$$

Thinking about transfers

- Assume for the moment we cannot directly identify poor households (i.e., no targeting)
- Besley and Kanbur (1988): How do we evaluate subsidies in terms of poverty reductions?
  - Infra-marginal subsidies
    - To everyone
    - With geographical targeting
  - Marginal subsidies (i.e., price changes)
    - To everyone
    - When there are both producers and consumers
- What goods would you want price subsidies on? Inferior goods. Why?
- Why are price subsidies worse in general? Why is a gasoline subsidy a bad idea? Distortions, positive Engel curves.
- Why might they be better?

Subsidies are still quite relevant



UBIs

Hanna and Olken 2018: Universal Basic Incomes vs. Targeted Transfers: Anti Poverty Programs in Developing Countries

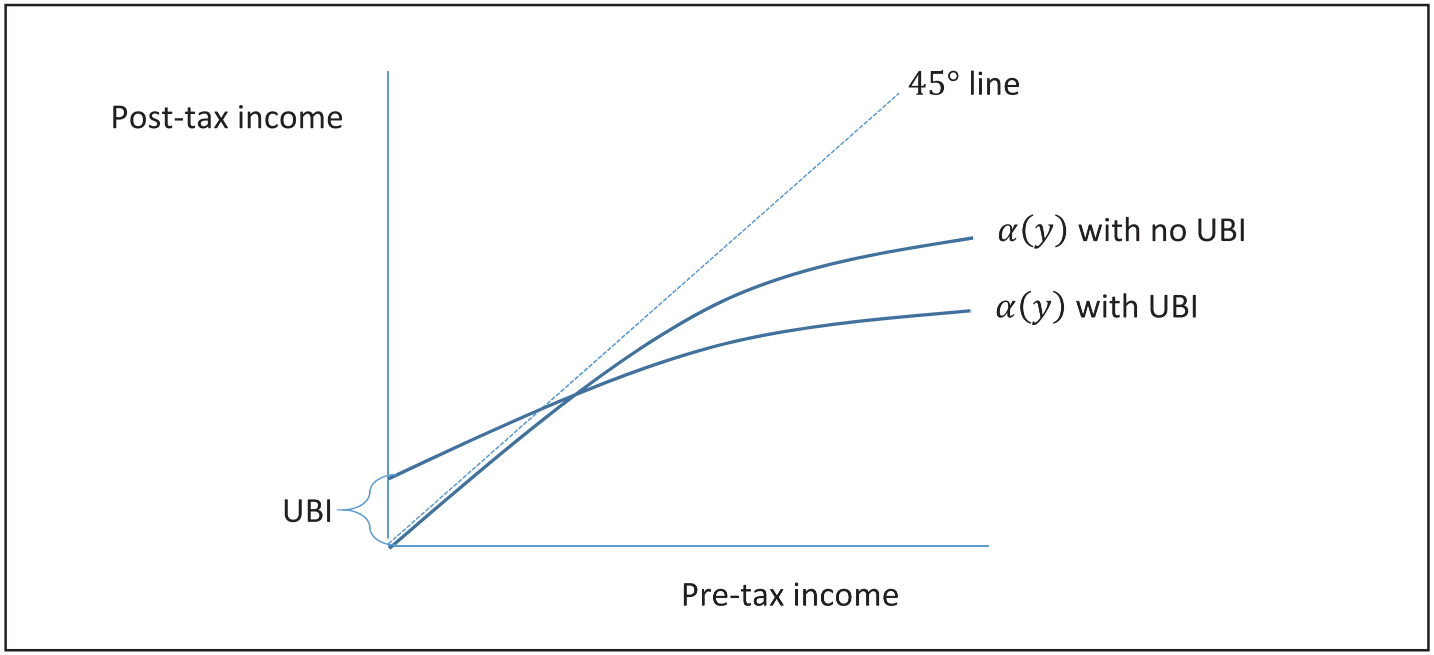
- Given subsidies are distortionary, many people have begun to advocate universal cash transfers
- No price effects, and labor supply effects likely small (Banerjee, Hanna, Kreindler, and Olken 2017)
- Comparatively simple - but needs two things to function
  - A system of unique IDs so nobody receives the transfer twice
  - A mechanism to handout the cash that works everywhere (even rural, remote areas)
- How can this be redistributive?

Conceptual framework

- Suppose pre-tax income is y
- Define after-tax-and-transfer income as $\alpha(y)$.
- Then any tax-and-transfer system that features $\alpha(0) > 0$ can be thought of as featuring a UBI
- Saez (2002) discusses this in the US context
  - Key result: UBI is often optimal when intensive labor supply elasticity is larger than extensive labor supply elasticity.
- How does this differ for developing countries?
  - Jensen 2016: most people don't pay taxes.
  - So if you set $\alpha(0) > 0$ you need to give that same transfer much further up the income distribution

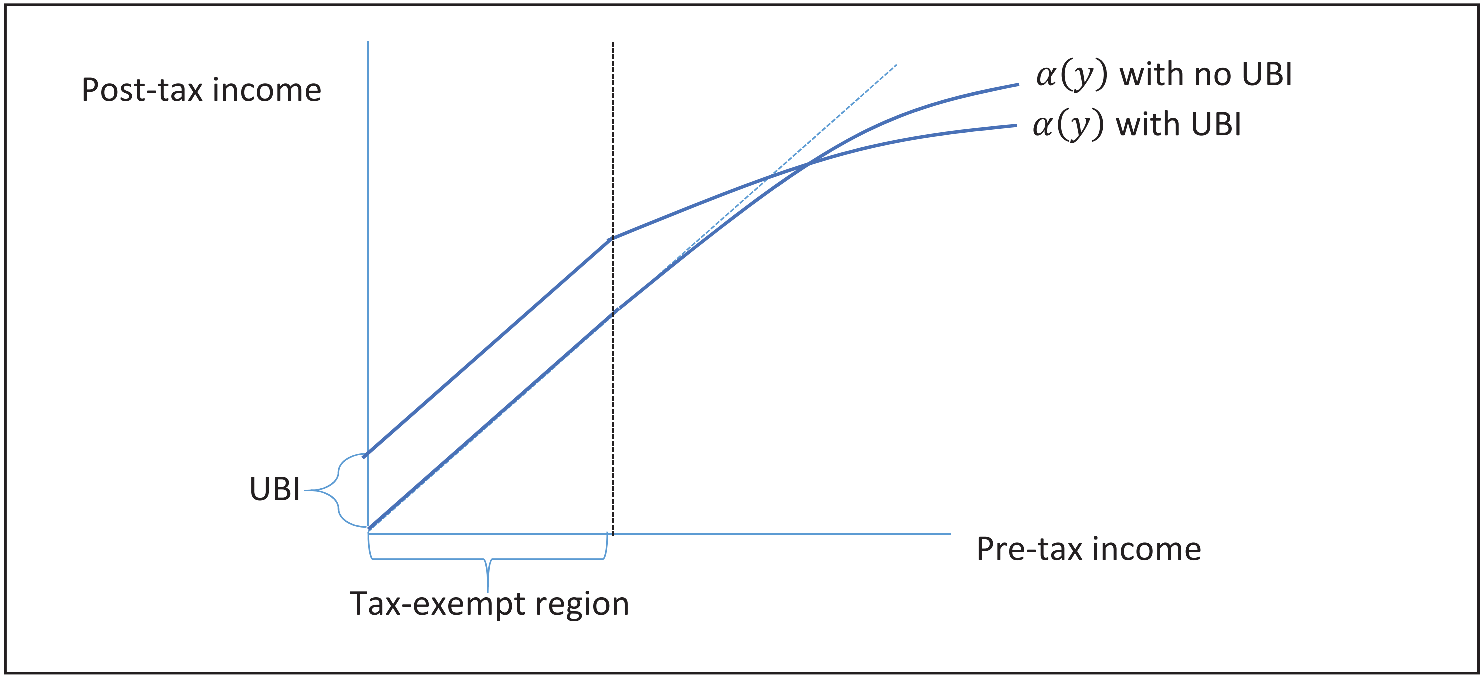
Developed countries

Figure 1: Example of Progressive Post-Tax Income Schedules With and Without a Universal Basic Income



Developing countries

Figure 2: Example of Post-Tax Income Schedules with and Without a Universal Basic Income, With a Tax-Exempt Region



Tradeoffs

- We then simulate welfare gains to contrast UBI vs targeted transfers
- More details later, after we discuss targeting...

Targeting

- Nevertheless most programs rely on targeting
- Targeting options if income is not observable:
    - Proxy-means tests (more generalized version of “tagging”)
    - Community-based targeting
    - Self-targeting

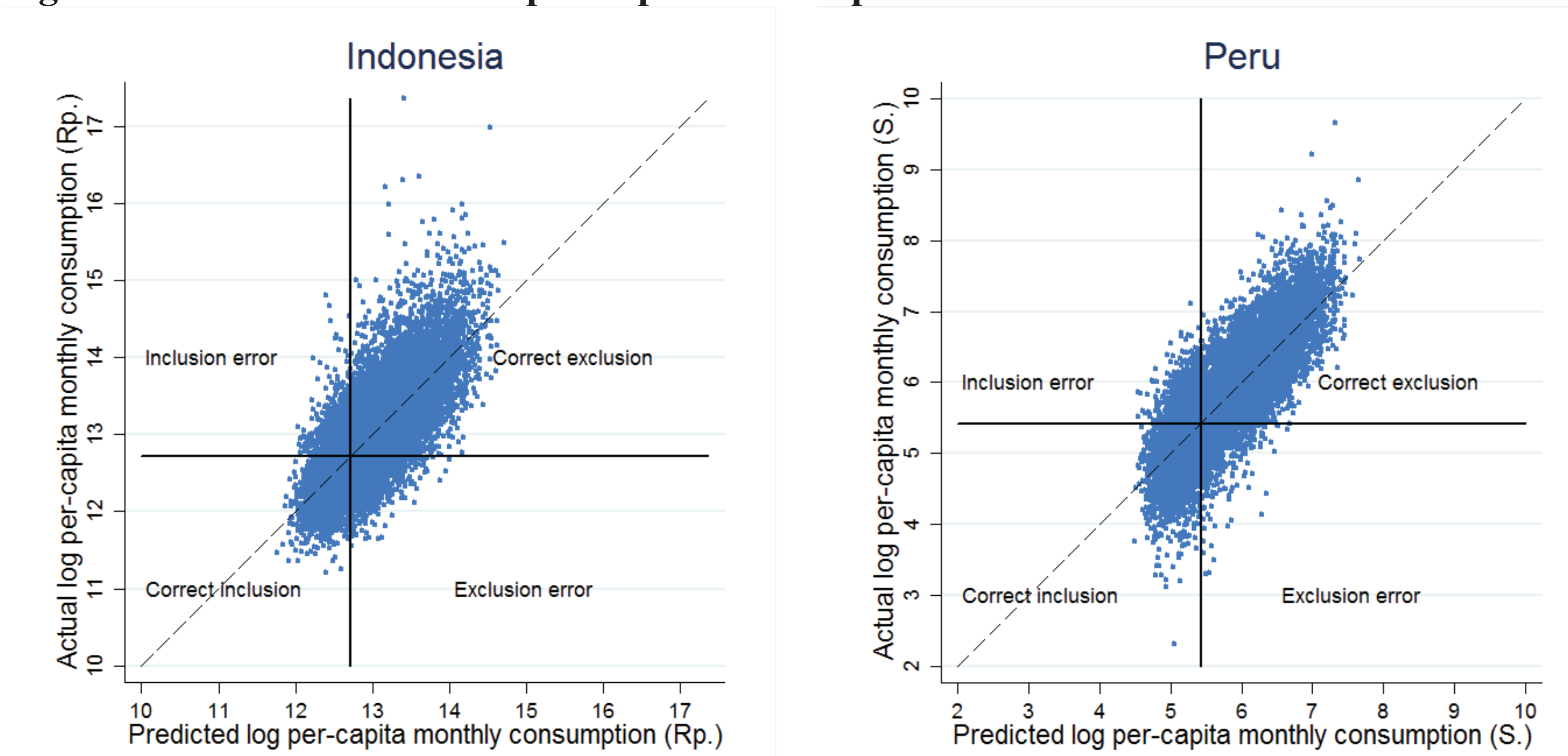
Proxy-Means Tests

- Similar idea to poverty mapping, but at individual level. This is the main way individual targeting is done in most developing countries (e.g., Progresa).
- Concept: consumption surveys are expensive, and non-verifiable, so you can't use them to target directly
- Instead: do a survey where you collect data on assets (land, house, motorcycle, etc.)
    - Assets capture permanent component of income
    - And they are hard to falsify on a survey
- Use survey data to estimate relationship between consumption and assets, and used predicted consumption for targeting
- Problems
    - R^2 much less than 1, so you don't get poverty exactly right (horizontal equity)
    - Corruption among surveyors
    - Costly: need to do a census (but not that costly)

Example of PMT prediction

From Hanna and Olken 2018

Figure 3: Predicted vs. actual per-capita consumption in test set data



Community-Based

- Allow local community to identify poor households
- Idea: local community has much more information than central government
  - This is the premise behind informal insurance, microfinance, etc.
- Problem:
  - If you are using this information to target beneficiaries, this information may not get revealed. Instead, elites may capture the project
  - Potential tradeoff: better local information vs. more elite capture
- Some existing evidence that communities do know more (Alderman, Galasso and Ravallion)

Comparing PMT and Community Approaches

Alatas, Banerjee, Hanna, Olken, and Tobias (2012): "Targeting The Poor: Evidence from a Field Experiment in Indonesia"

- Randomized experiment compares three targeting methods:
  - Proxy-means test
  - Community ranking
  - Hybrid: community ranking, followed by proxy-means test on bottom 50% (to prevent elite capture)
- Villages randomized to one of above treatments, used to give out real one-time \$3 transfer
- Sub-treatments to tease out why community and PMT may differ
  - Elite capture: let elites run meetings or invite full community
  - Effort: randomize order of ranking and see if going first matters, start with identifying 10 poorest first
  - Preferences: vary time of meeting to encourage more women in some meetings
- Baseline survey to measure true consumption, endline to measure satisfaction with targeting

Community treatment

Community treatment

Experimental design

TABLE 1—RANDOMIZATION DESIGN

Community/hybrid subtreatments			Main treatments		
			Community	Hybrid	PMT
Elite	10 poorest first	Day	24	23	
		Night	26	32	
	No 10 poorest first	Day	29	20	
		Night	29	34	
Whole community	10 poorest first	Day	29	28	
		Night	29	23	
	No 10 poorest first	Day	28	33	
		Night	20	24	
		Total	214	217	209

Metrics

- First evaluate targeting based on headcount:
  - $MISTARGET = 0$ if poor and didn't receive transfer or rich and did receive it, 0 otherwise
- Evaluate targeting results based on four metrics:
  - Consumption (u_g)
  - How households ranked each other on baseline survey (u_c)
  - How village head ranked households at baseline (u_e)
  - Self-assessment (u_s)
- Also evaluate impact on satisfaction and legitimacy (many different measures)

Specification

- For mistargeting:

$$MISTARGET_{vhk} = \alpha + \beta_1 COMMUNITY_{vhk} + \beta_2 HYBRID_{vhk} + \gamma_k + \varepsilon$$

- Rank-correlations:
  - Convert each metric to a rank-ordering within village
  - Each targeting treatment defines a rank-ordering within village
  - So for each village v, compute $RANKCORR_{vkw}$ as the correlation between the targeting outcome in village v and welfare metric w
- Then regress

$$RANKCORR_{vkw} = \alpha + \beta_1 COMMUNITY_{vk} + \beta_2 HYBRID_{vk} + \gamma_k + \varepsilon$$

Results on mistargeting (headcount)

TABLE 3—RESULTS OF DIFFERENT TARGETING METHODS ON ERROR RATE BASED ON CONSUMPTION

		By income status		By detailed income status				
Sample:	Full population (1)	Inclusion error (2)	Exclusion error (3)	Rich (4)	Middle income (5)	Near poor (6)	Very poor (7)	Per capita consumption of beneficiaries (8)
Community treatment	0.031*	0.046**	0.022	0.028	0.067**	0.49	−0.013	9.933
	(0.017)	(0.018)	(0.028)	(0.021)	(0.027)	(0.038)	(0.039)	(18.742)
Hybrid treatment	0.029*	0.037**	0.009	0.020	0.052**	0.031	−0.008	−1.155
	(0.016)	(0.017)	(0.027)	(0.020)	(0.025)	(0.037)	(0.037)	(19.302)
Observations	5,753	3,725	2,028	1,843	1,882	1,074	954	1,719
Mean in PMT treatment	0.30	0.18	0.52	0.13	0.23	0.55	0.48	366

Results on alternative welfare metrics

- Communities target worse based on consumption, but target better based on local welfare metrics

TABLE 9—ASSESSING TARGETING TREATMENTS USING ALTERNATIVE WELFARE METRICS

	Consumption (r_g) (1)	Community survey ranks (r_c) (2)	Subvillage head survey ranks(r_e) (3)	Self-assessment (r_s) (4)
Community treatment	−0.065**	0.246***	0.248***	0.102***
	(0.033)	(0.029)	(0.038)	(0.033)
Hybrid treatment	−0.067**	0.143***	0.128***	0.075**
	(0.033)	(0.029)	(0.038)	(0.033)
Observations	640	640	640	637
Mean in PMT treatment	0.451	0.506	0.456	0.343

Results on satisfaction and legitimacy

- All metrics of satisfaction are higher with community treatment

TABLE 6—SATISFACTION

Panel A. Household endline survey

	Is the method applied to determine the targeted households appropriate? (1 = worst, 4 = best) (1)	Are you satisfied with the targeting activities in this subvillage in general? (1 = worst, 4 = best) (2)	Are there any poor HH that should be added to the list? (0 = no, 1 = yes) (3)	Number of HH that should be added to list (4)	Number of HH that should be subtracted from list (5)	p-value from joint test (6)
Community treatment	0.161***	0.245***	−0.189***	−0.578***	−0.554***	< 0.001
	(0.056)	(0.049)	(0.040)	(0.158)	(0.112)	
Hybrid treatment	0.018	0.063	0.020	0.078	−0.171	0.762
	(0.055)	(0.049)	(0.042)	(0.188)	(0.129)	
Observations	1,089	1,214	1,435	1,435	1,435	
Mean in PMT treatment	3.243	3.042	0.568	1.458	0.968	

Summary

- Interpretation: community has different concept of welfare, and community targeting allows them to achieve it. Outcome matches local welfare function, hence higher satisfaction.
- Other results:
  - Elite capture: no elite capture
    - Elite connected households no more likely to get transfer
    - In fact, if anything reverse discrimination in community treatment
    - But might be different if more money were at stake
  - Information:
    - Communities have some information about that PMT does not
- Conclusions:
  - Suggests that tradeoff for community targeting is more about what welfare function you want to maximize
    - If your goal is to minimize poverty headcount, want to use PMT
    - If your goal is to maximize utility (ie.., $W = W(u_1, u_2, ..., u_n)$), then community approach may be better

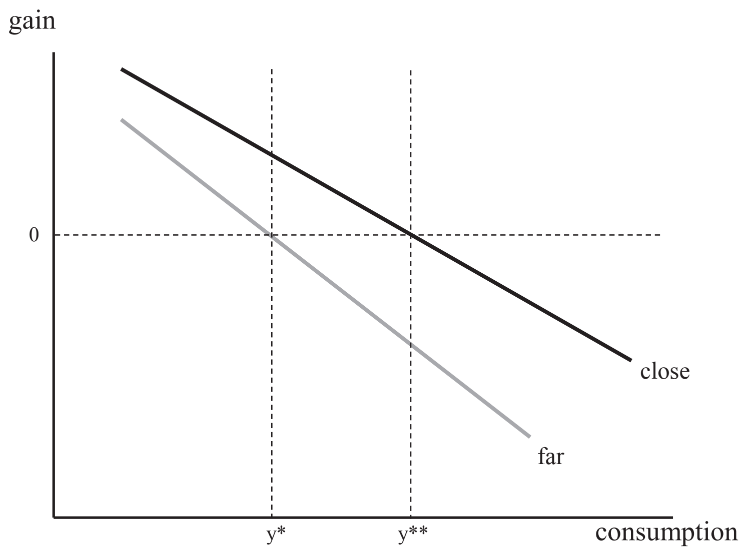
Self-Targeting

- Nichols and Zeckhauser (1982): "Ordeals" can be used to target the poor
  - Suppose you need to wait in long line to get unemployment benefits
  - Unemployed have low opportunity cost of time, so they are more likely to wait in line
  - Waiting in line therefore serves as a screening device

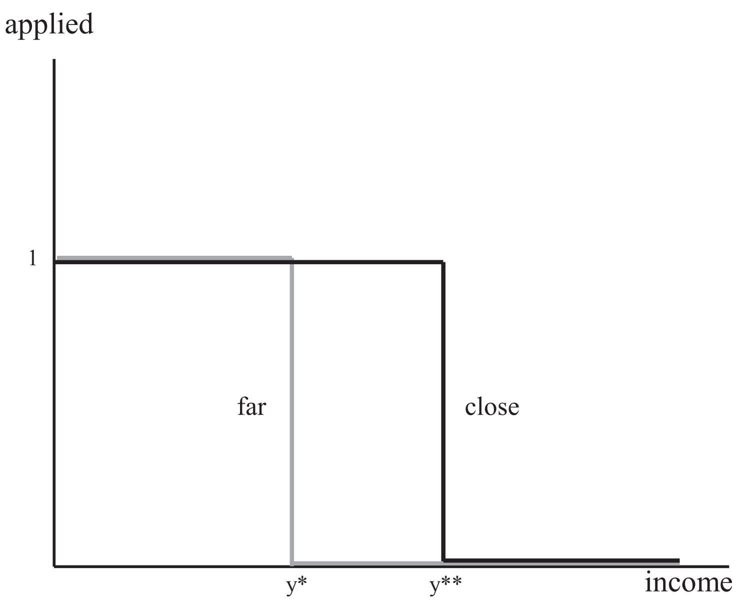
Simple self-targeting model

Alatas et al 2012: "Ordeal Mechanisms in Targeting: Theory and Evidence from Indonesia"

Figure 1. 1Illustration of utility gain with no errors



(a) Gain vs. consumption for close and far subtreatments



(b) Targeting improves as length of ordeal increases

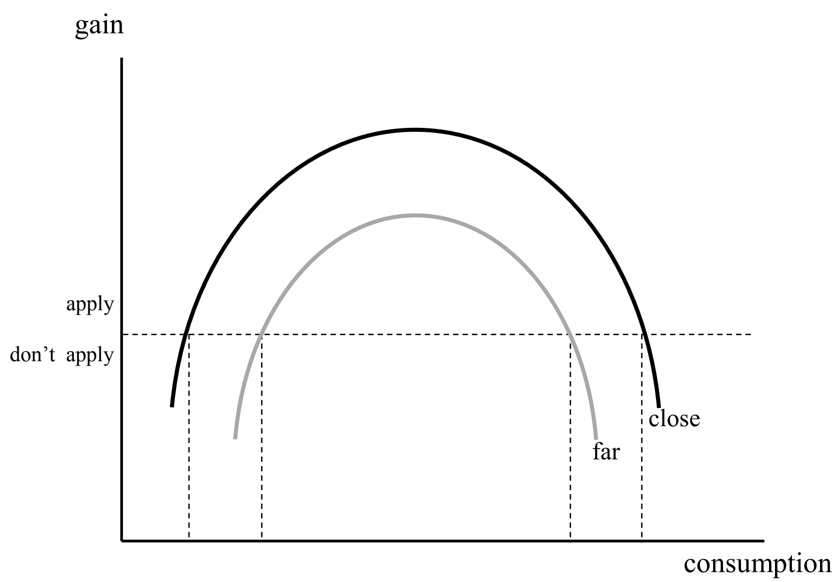
Self-Targeting Theory

- But in fact, it may be more complicated than that. Theoretical reasons?
  - Just because poor have lower monetary cost does not mean they have lower utility cost
  - Rich and poor may have different technologies for overcoming ordeal (walk vs. drive)
  - Distribution of idiosyncratic shocks

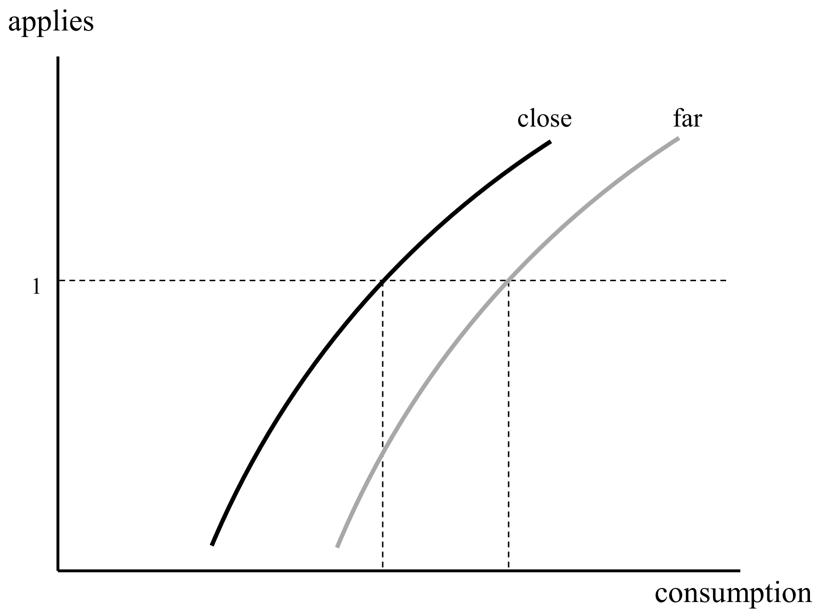
Differential utility

Alatas et al 2012: "Ordeal Mechanisms in Targeting: Theory and Evidence from Indonesia"

FIGURE 4. Illustration of utility gain with concave utility



(A) Gain vs. consumption for close and far subtreatments

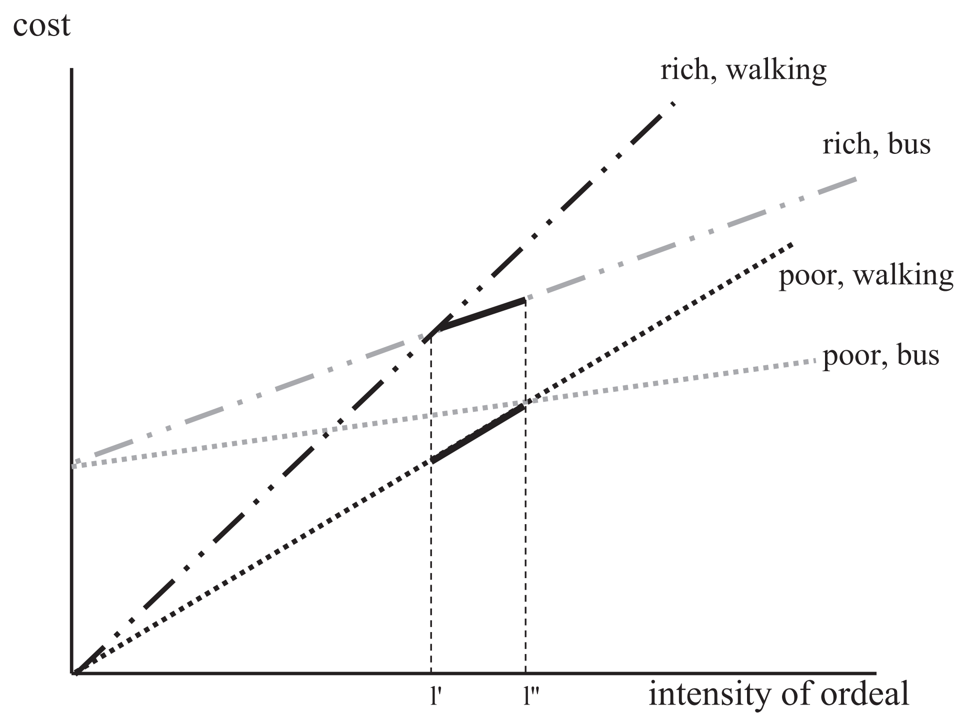


(B) Targeting can worsen as length of ordeal increases

Travel costs

Alatas et al 2012: "Ordeal Mechanisms in Targeting: Theory and Evidence from Indonesia"

FIGURE 3. Non-Linearities in Travel Costs

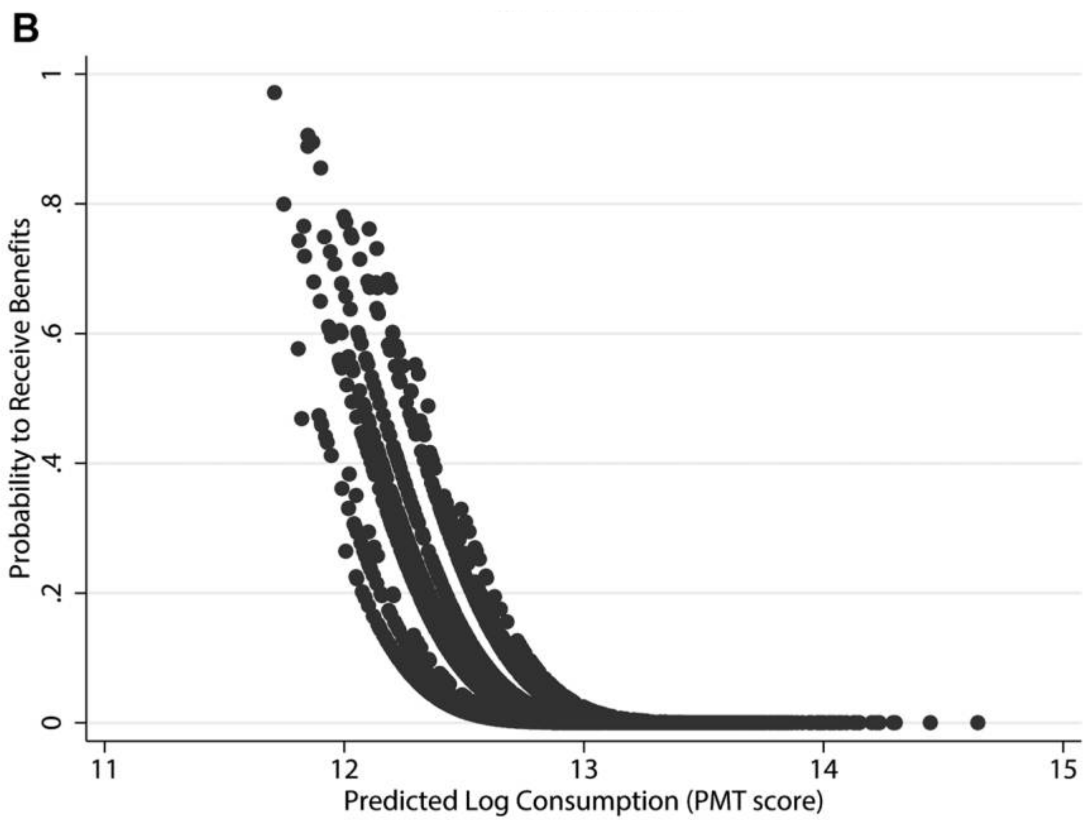


Applying this to a targeting program

- All of the above was true if you paid a time cost and got the benefit for sure
- What happens though if you need to pay a time cost just to apply for a program?
- In our example: after showing up and applying, you are still subject to the PMT. This means that you need to forecast your likelihood of surviving.
- This changes the model in several important ways
  - Sophisticated households understand how the PMT works. For them, rich households don't bother to apply because they know they are unlikely to get the program. Saves the government the hassle of screening them – and improves targeting because those rich households where the PMT would make a mistake self-select out.
  - Naive households don't understand the PMT. They just know their income. Here, self-selection improves PMT further because they are selecting based on y, not $X'\beta$.

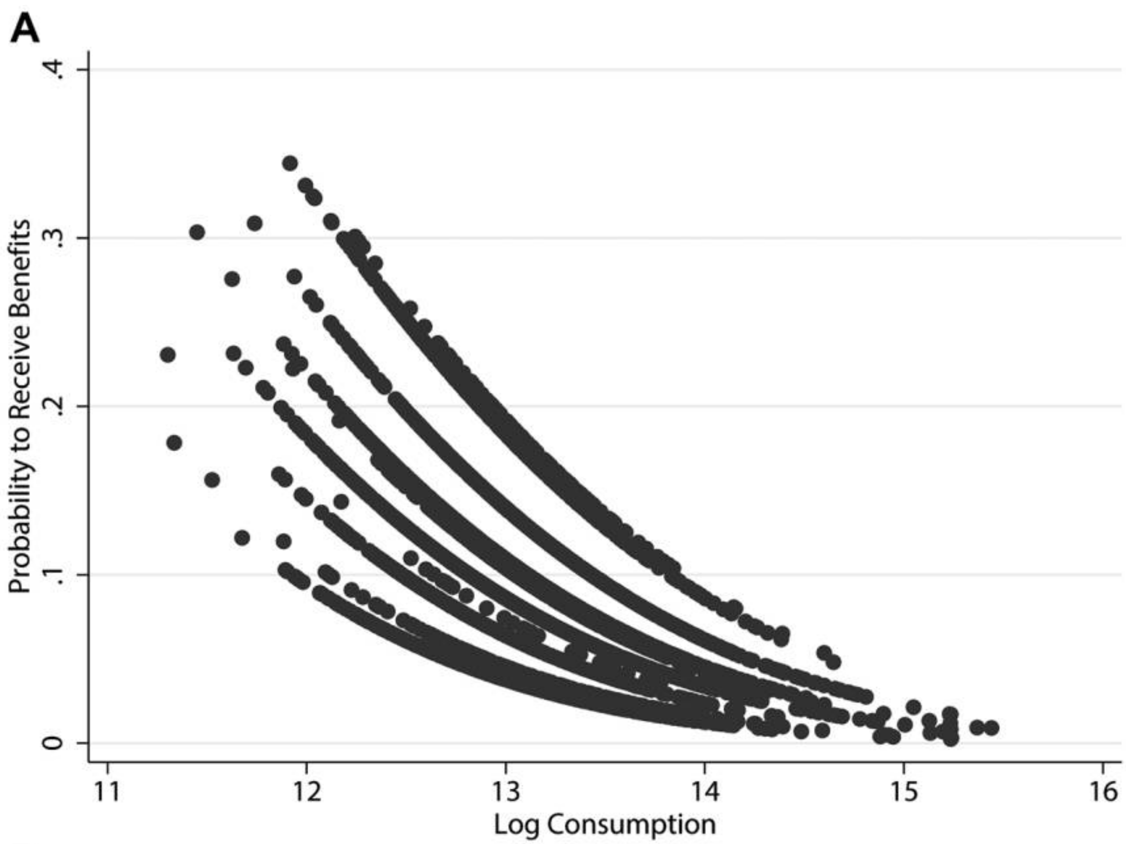
Success rates conditional on applying

Sophisticated households: success vs. PMT score



Success rates conditional on applying

Naiive households: success vs. consumption



Model

- In each period households get linear utility from current period consumption x. Preferences are additively separable in present and future utility. Discount factor δ.
- Flow income of y in each period. No saving. Denote by y^o the portion of income observable by government.
- Households decide whether to sign up by balancing costs of signing up with discounted future benefits of getting the program
  - Monetary cost of signing up is $c(l, y)$ where l is distance to the place where you sign up (more on this later).
  - For sophisticated households, if they sign up, get benefit b with probability $\mu(y^o)$ (and zero otherwise).
  - For unsophisticated households, if they sign up, get benefit b with probability $\lambda(y)$ (and zero otherwise).
- Households get utility shock ϵ if register, distributed $F(\epsilon)$.

Model

- Expected gain from showing up to apply for sophisticated and unsophisticated households is therefore:

$$g(y^o, y, l) = -c(l, y) + \mu(y^o)\delta b + \epsilon \qquad \text{(sophisticated)}$$
$$h(y, l) = -c(l, y) + \lambda(y)\delta b + \epsilon \qquad \text{(naiive)}$$

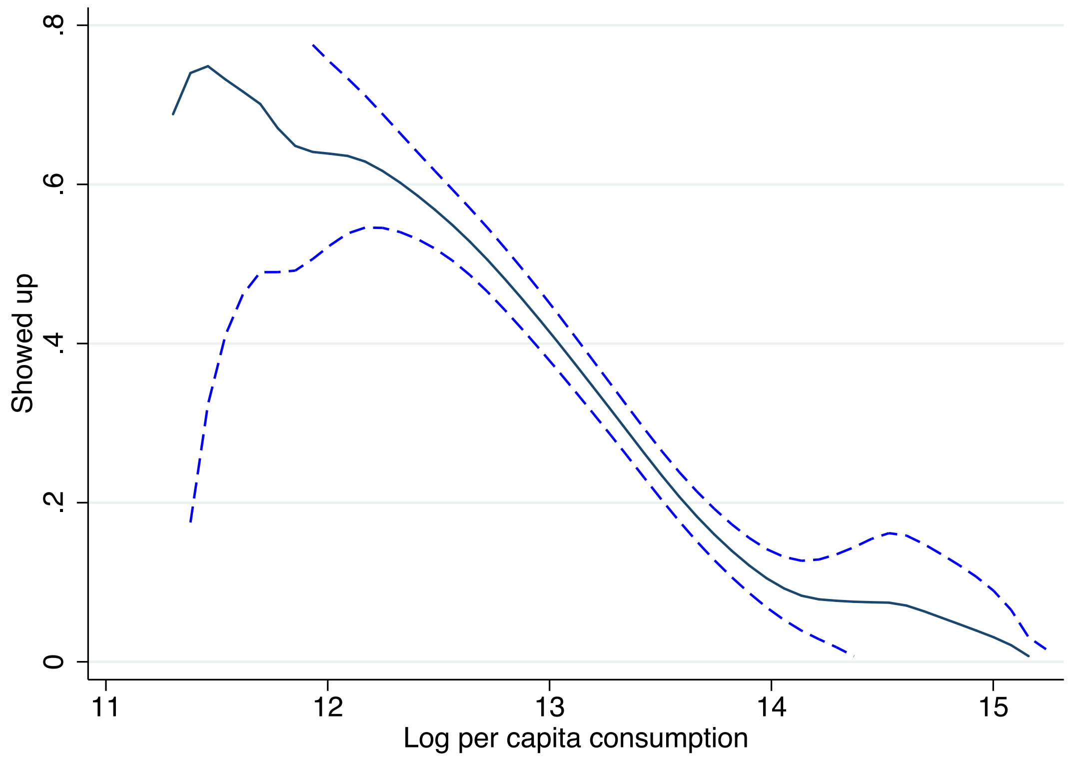
- Denote by α the share of sophisticated households
- To close the model need to assume that the $\lambda(y)$ function is correct given the underlying PMT process μ and the composition of who applies in equilibrium

Experiment

- Investigate this using a randomized experiment in Indonesia
- 400 villages newly eligible for Indonesian CCT. Targeted to bottom 10% of HH based on PMT
- Randomized into PMT (with some pre-screening done by villages) vs. self-targeting, where you had to go to central meeting place to apply for program
- Also varied distance to application site and opportunity cost of applying
- Investigate who signed up, compare experimentally to PMT, and then estimate the model structurally to tease apart which of the theoretical mechanisms ideas above was important

Who shows up

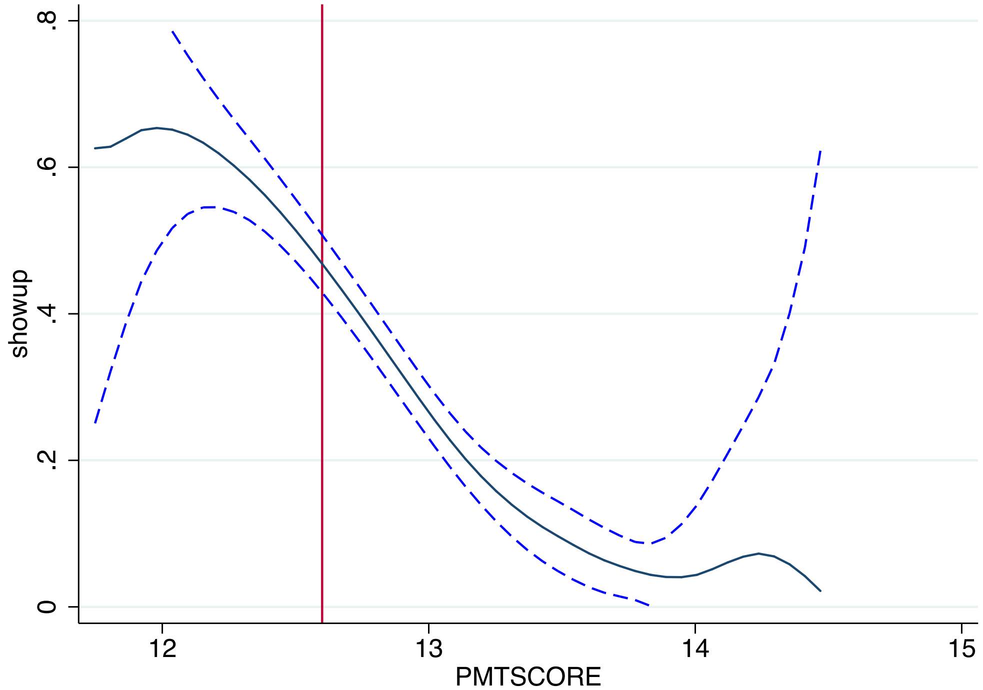
Figure 5. Showup Rates Versus Log Per Capita Consumption



- Aside: this is a Fan regression. What is that?

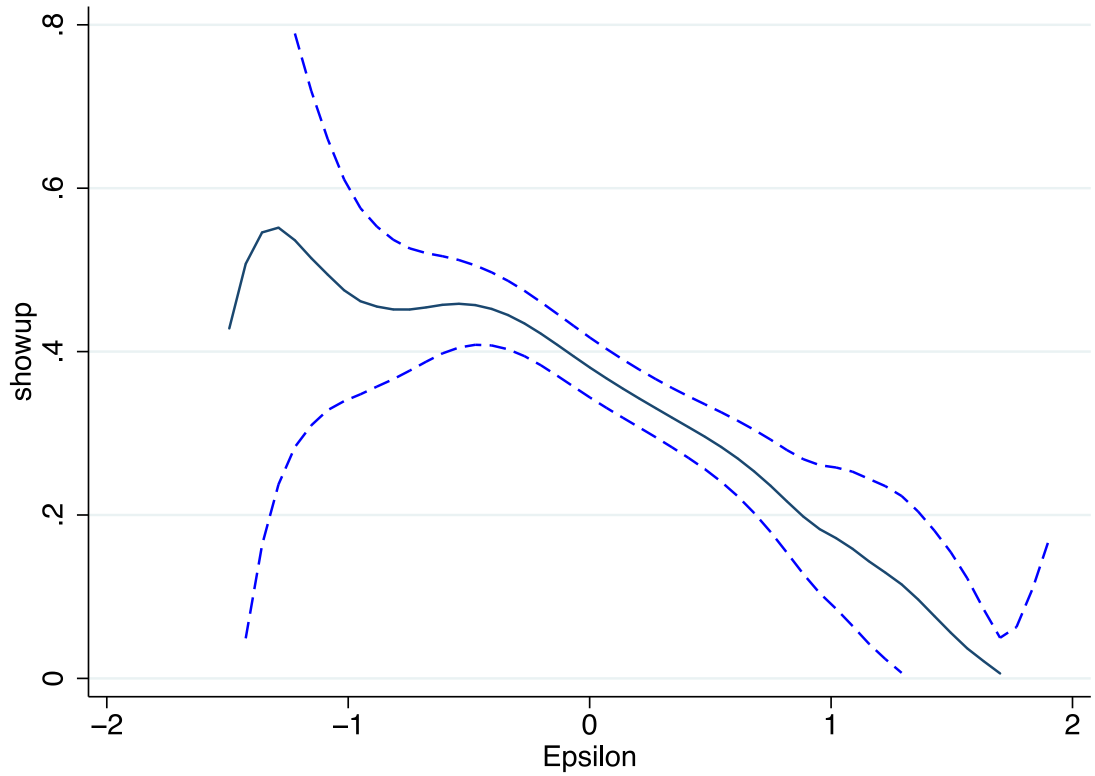
On observables...

Figure 6. Showup Rates Versus Observable and Unobservable Components of Log Per Capita Consumption



(a) Showup as a function of observable consumption ($X_i'\beta$)

And unobservables...



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(B) Showup as a function of unobservable consumption (ε_i)

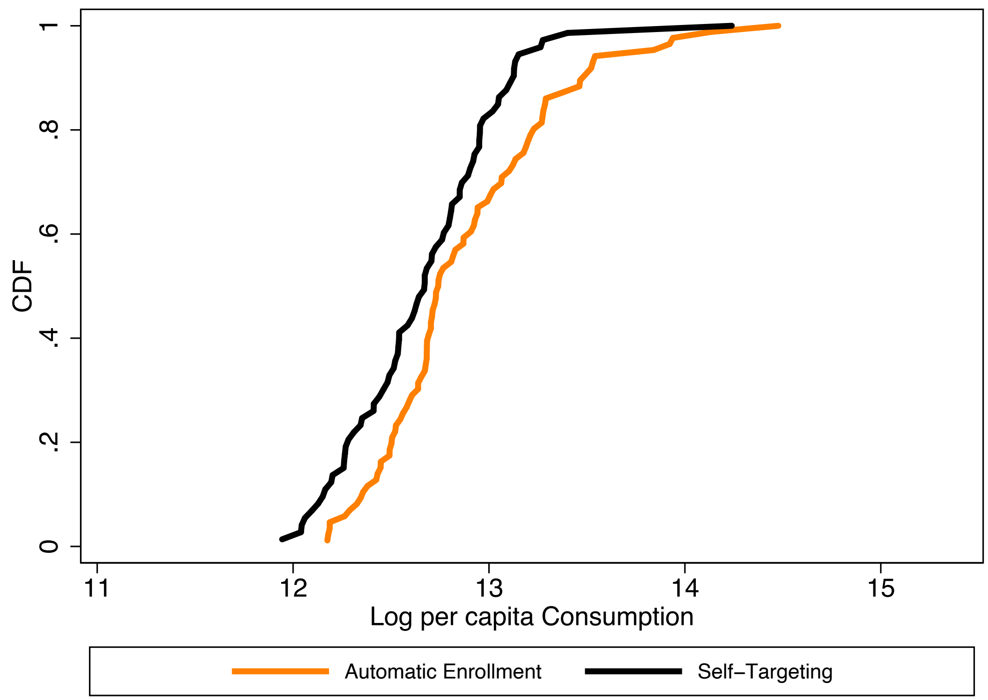
Selection on both observables and unobservables

TABLE 4
PROBABILITY OF SHOWING UP AS A FUNCTION OF THE OBSERVED AND UNOBSERVED COMPONENTS OF BASELINE LOG PER CAPITA CONSUMPTION

	Showed Up		
	All (1)	Very Poor (2)	Not Very Poor (3)
Observable consumption (y_i^o)	−2.217***	−.325	−2.310***
	(.201)	(1.785)	(.208)
Unobservable consumption (y_i^u)	−.907***	−.775	−.908***
	(.136)	(.581)	(.138)
Stratum fixed effects	No	No	No
Observations	2,000	114	1,886
Mean of dependent variable	.377	.658	.360

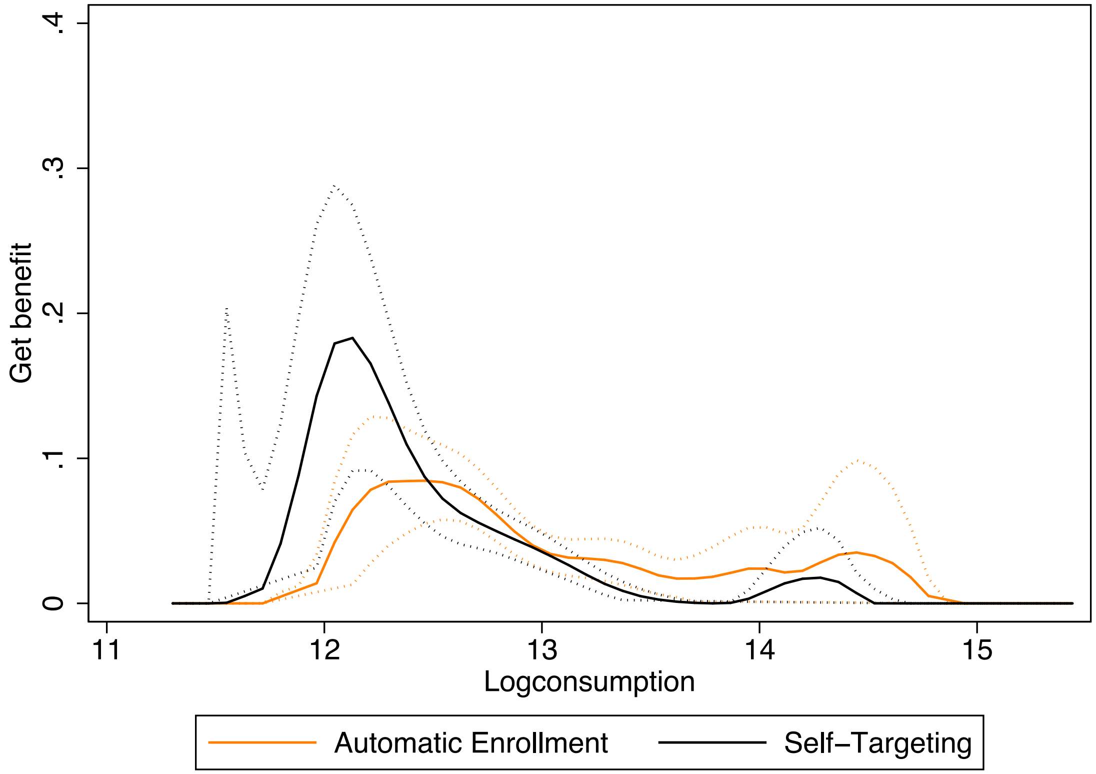
Comparison to actual (pre-selected) PMT...

FIGURE 7. Experimental Comparison of Self Targeting and Automatic Enrollment Treatments



(A) CDF of log per capita consumption of beneficiaries

Comparison to actual (pre-selected) PMT...



(B) Receiving benefit as a function of log per capita consumption

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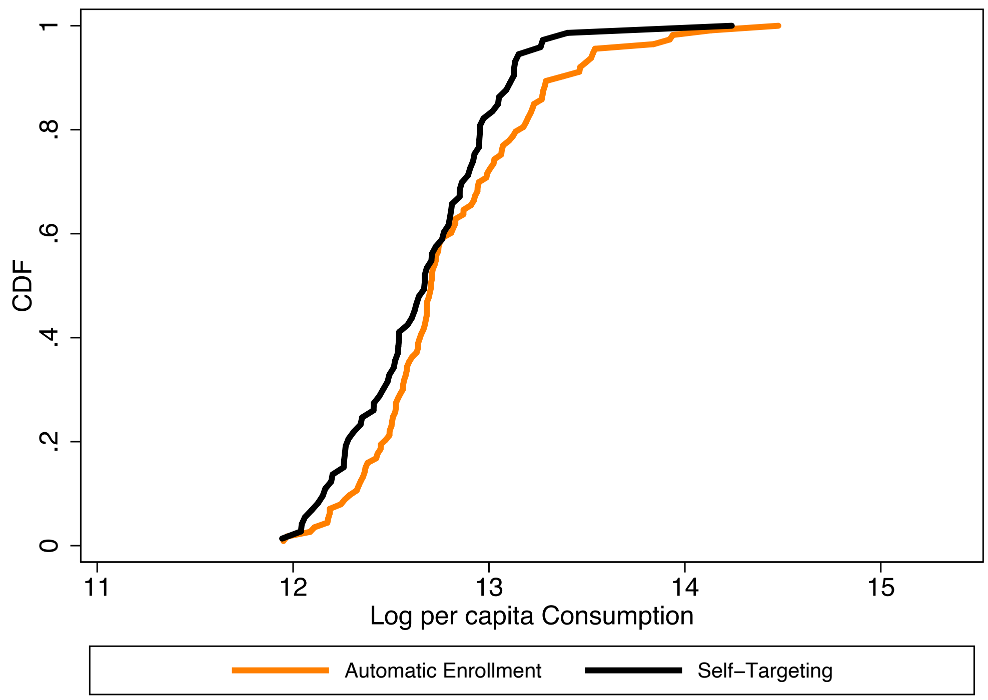
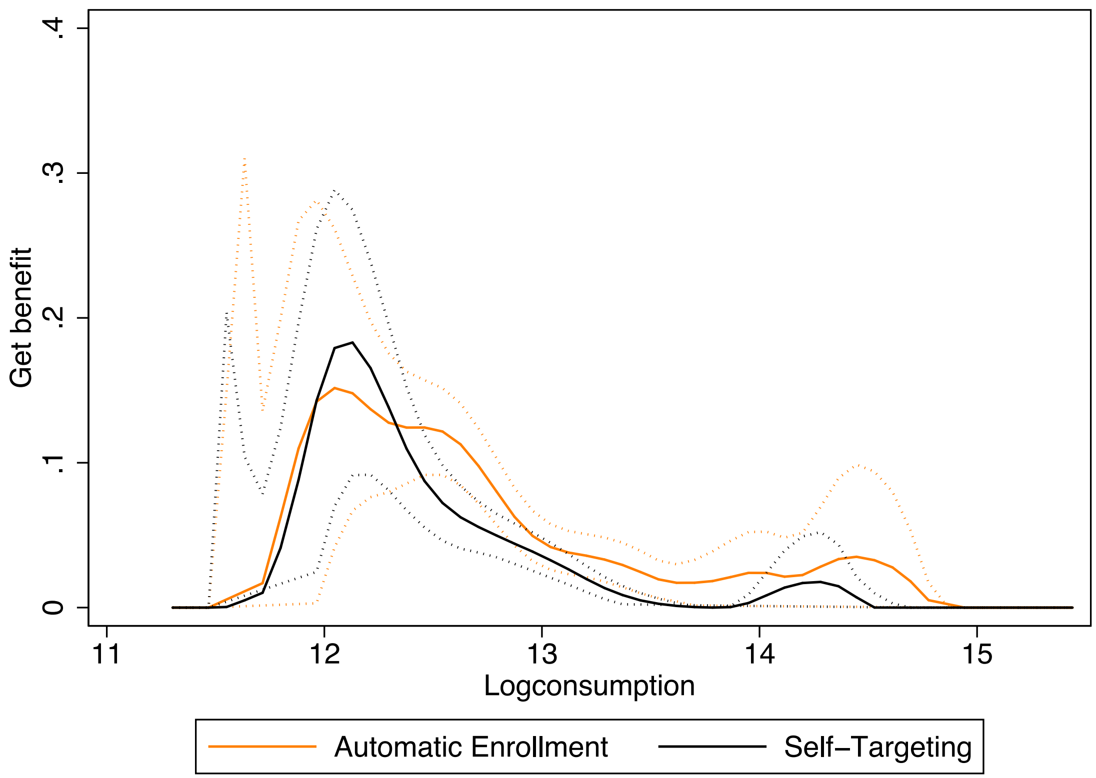
Comparison to hypothetical universal PMT...

Figure 8. Comparison of Self-Selection and Hypothetical Universal Automatic Enrollment



(a) CDF of consumption of beneficiaries

Comparison to hypothetical universal PMT...



(B) Getting benefit as a function of log per capita consumption

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Estimating the model

- Many forces could explain improvements. Which is most important?
- To investigate this, we estimate the model
  - Use empirically estimated cost function $c\left(y_i, l_i\right) = wage_i * \left(traveltime_i + \overline{waittime}\right) + travelmoney_i$, empirically estimated μ_i and expected benefits b_i
  - Assume consumption y is measured with lognormal error ω, with $Var(\omega)$ estimated from short panel data
  - Parametrize $\lambda(y)$ as Probit, so $\lambda(y) = \Phi(\gamma + \pi y)$
  - Unknown parameters are α (share sophisticated), mean/variance of utility shocks ϵ, and two parameters of λ distribution (γ and π)
  - This yields

$$\begin{aligned} Prob(showup_i = 1) = \alpha \int Prob\left(\varepsilon > -g(y_i^o e^{\omega}, y_i e^{\omega}, l_i)\right) df_{\omega} \\ +(1-\alpha) \int Prob\left(\varepsilon > -h(y_i e^{\omega}, l_i)\right) df_{\omega} \end{aligned}$$

Structural models and GMM

- You hear a lot about structural models. What is this?
- Recall we have a model, which generates $Prob(showup_i = 1)$ as a function of individual i's characteristics and some parameters – in our case, α (share sophisticated), mean/variance of utility shocks ϵ, and two parameters of λ distribution (γ and π)
- Structural estimation just says – what values of $\alpha, \mu_\epsilon, \sigma_\epsilon, \gamma, \pi$ best get $Prob(showup_i = 1)$ in the model to match $Prob(showup_i = 1)$ in the actual data
- To do this, you define *moments*. These are just statistics of the data that you can also calculate in the model generated data.You need at least as many moment as parameters, but you can have more.
- You then search for the set of parameters $\alpha, \mu_\epsilon, \sigma_\epsilon, \gamma, \pi$ so that the moments from the model are as close as possible to the moments from the data. That's it; all the rest is commentary.
  - One important piece of commentary: what if you have more moments than parameters (over-identified)?
  - GMM tells you how to weight the moments optimally, based on how helpful they are to identify the parameters

Using the model to understand the results

- *Different technologies for overcoming ordeals*: we regress average money costs and travel time on quadratic in distance, and assign everyone the same "travel" costs (i.e., constraining travel technologies to be the same for rich and poor)—fact that results look the same suggests that technology not an issue
- *Shocks*: Cutting variance in half suggests close/far would have about a 25% larger effect, but still not enough to be statistically detectable
- *Beliefs about passing test*: Eliminating difference in beliefs about passing asset test between rich and poor eliminates about 80 percent of the difference between rich and poor showup rates. So this is the main item.
- Key intuition: there are a large number of rich people. Individually, not rational to apply with small cost since probability they make it through the screen is small. So small costs screen them out. But since there are many such people relative to desired beneficiary, this leads to large improvements in targeting.

Results and counterfactuals

TABLE 9
Modeled Effects of Time and Distance Costs on Show-Up Rates

	Show-Up Rate (Experimental) (1)	Predicted Show-Up Probability (Model): Baseline Model (2)	$\sigma_\varepsilon = \hat{\sigma}_\varepsilon/2$ (3)	$\sigma_\varepsilon = 0$ (4)	Assuming Same Travel Technology (5)	Constant $\mu(\cdot)$ and $\lambda(\cdot)$ (6)
A. Logistic Regressions						
Close	1.509	−1.365	−1.825	−1.791	−1.367	−1.742
	(2.972)	(3.098)	(3.472)	(3.765)	(2.967)	(2.18)
Log consumption	−1.423***	−1.630***	−2.181***	−2.456***	−1.631***	−.103
	(.148)	(.163)	(.193)	(.204)	(.166)	(.118)
Close × log consumption	−.105	.105	.141	.138	.106	.136
	(.227)	(.238)	(.268)	(.29)	(.228)	(.166)
Observations	1,971	5,913,000	5,913,000	5,913,000	5,913,000	5,913,000
p-value		.522	.483	.509	.513	.391
B. Show-Up Rates						
Above poverty line, far	34.09	34.55	30.04	28.12	34.54	45.89
Above poverty line, close	38.99	37.37	33.11	31.17	37.37	47.15
Below poverty line, far	53.23	71.94	72.94	73.83	71.92	46.53
Below poverty line, close	59.32	65.52	65.81	66.25	65.52	43.84
C. Show-Up Rate Ratios						
Poor to rich ratio, far	1.561	2.082	2.428	2.626	2.082	1.014
	(.213)	(.203)	(.244)	(.262)	(.199)	(.14)
Poor to rich ratio, close	1.522	1.753	1.987	2.126	1.753	.93
	(.169)	(.183)	(.214)	(.221)	(.19)	(.141)
Difference of ratios	.040	.329	.441	.5	.329	.084
	(.268)	(.271)	(.322)	(.34)	(.281)	(.197)
p-value		.448	.338	.288	.456	.893

UBIs vs. targeted transfers

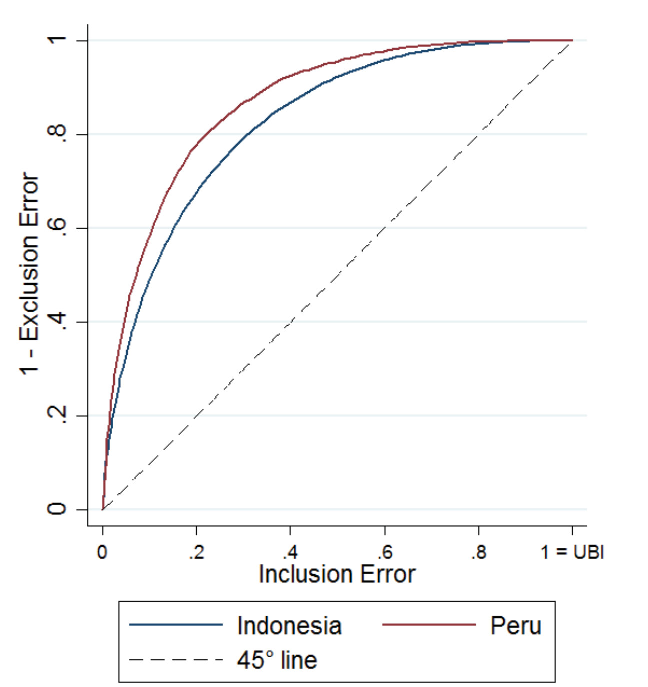
Simulations from Hanna and Olken (2018)

- OK, so now that we know about targeting, should we do it?
- Hanna and Olken (2018) run a simple welfare calculation
- Assume CRRA utility, so
$$U = \frac{\sum(y_i + b_i)^{1-\rho}}{1-\rho}$$
- Assume a fixed budget B, so as number of beneficiaries increases, b_i decreases
- Holding targeting constant, can then think of tradeoffs between inclusion error, exclusion error, welfare
- Can also calculate horizontal equity violations and implied tax rate

The PMT technology curve

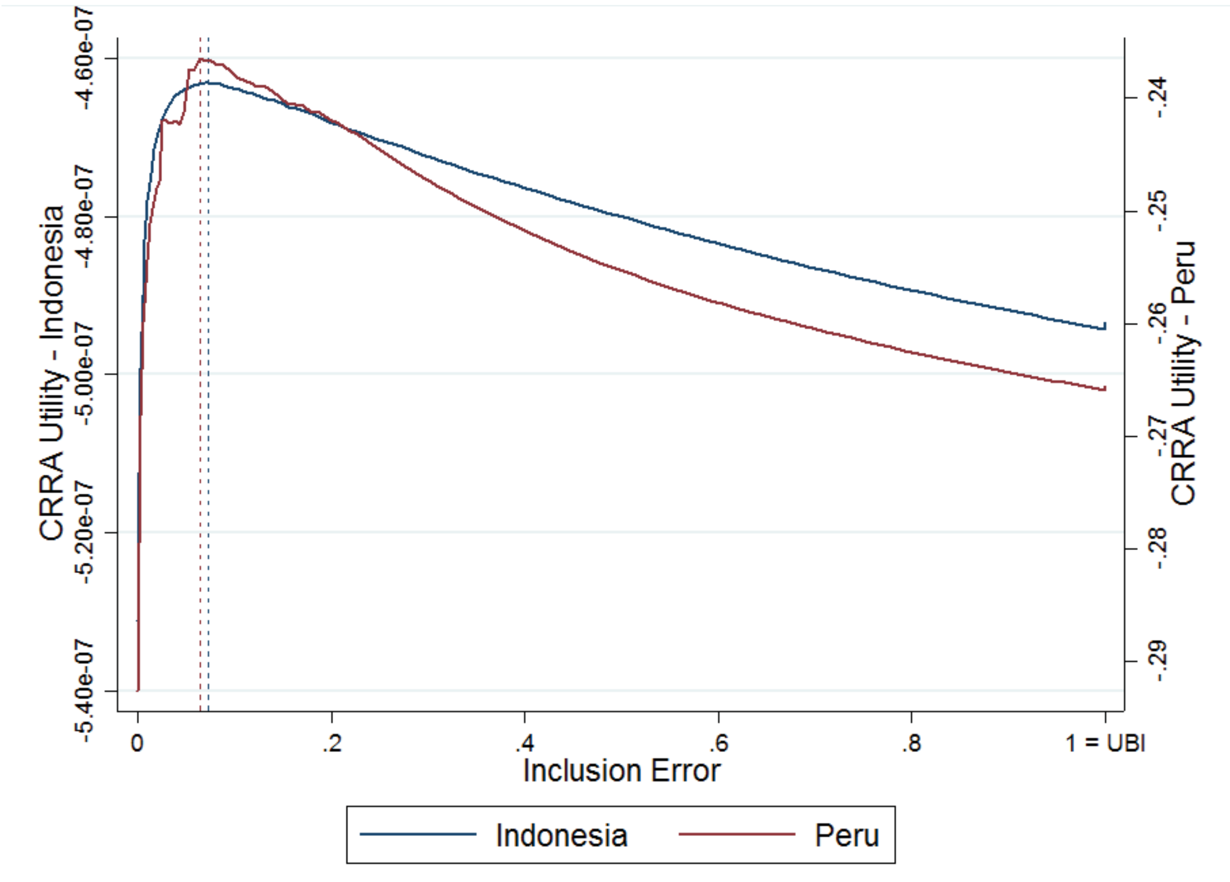
Figure 4: Tradeoffs between inclusion error and exclusion error by varying eligibility cutoff

Panel A: ROC Curves for Program Targeting



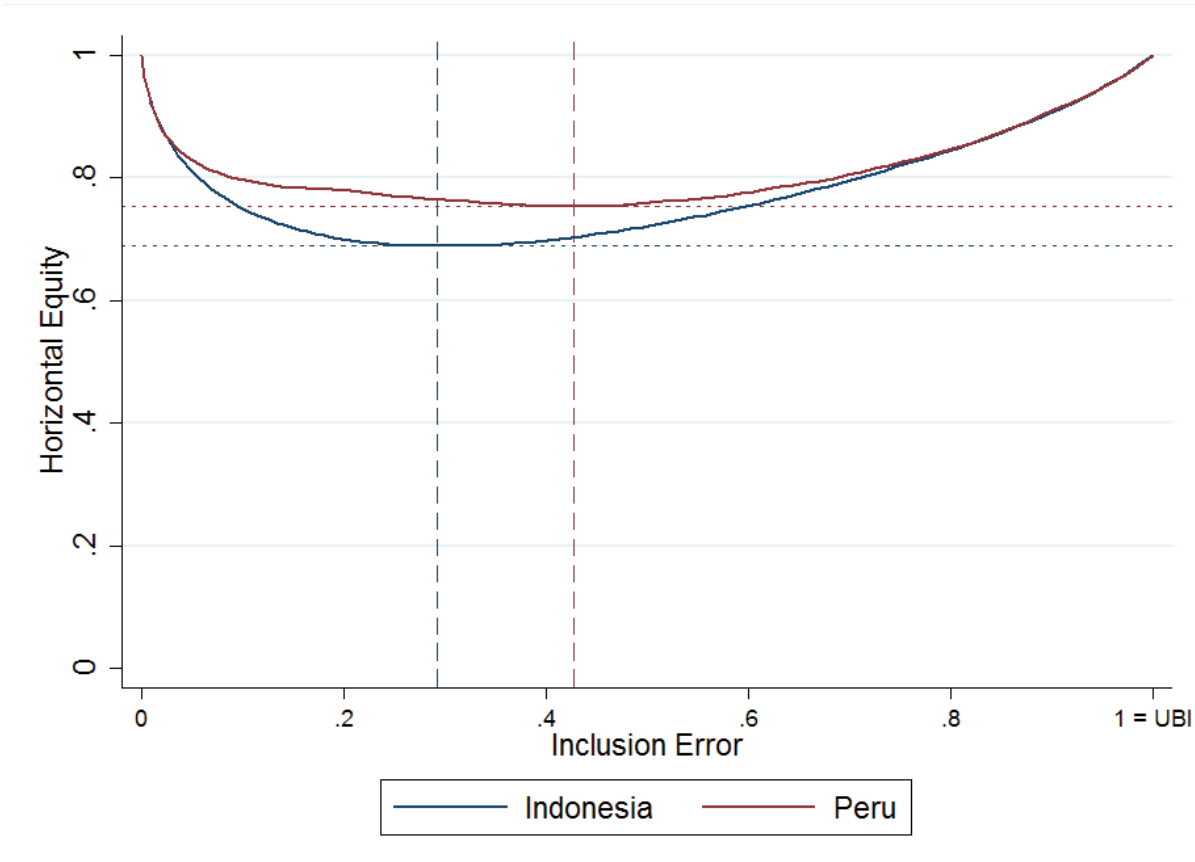
- Aside: this is an ROC curve. What is this?

Welfare

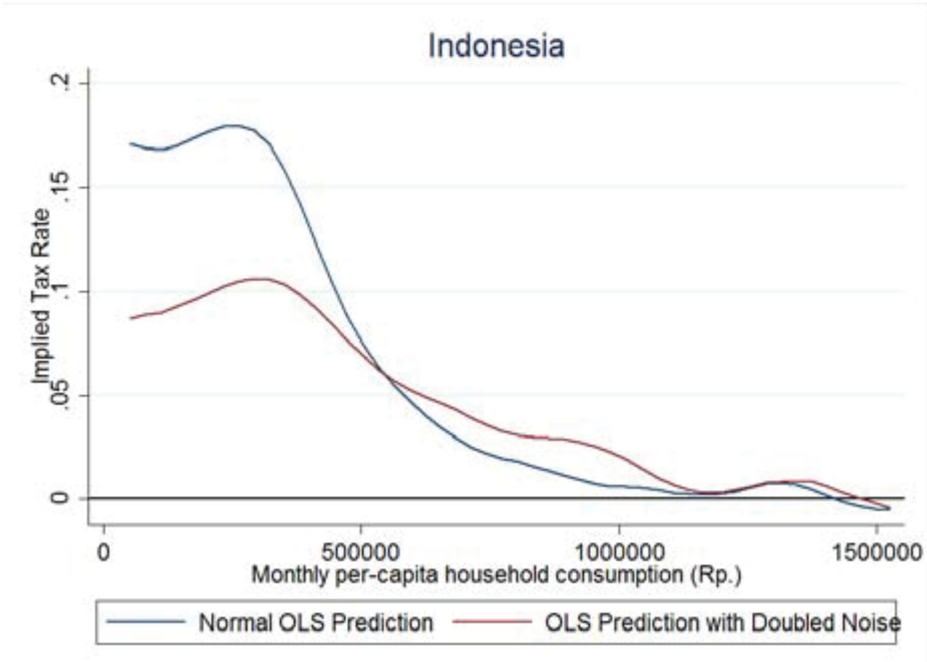


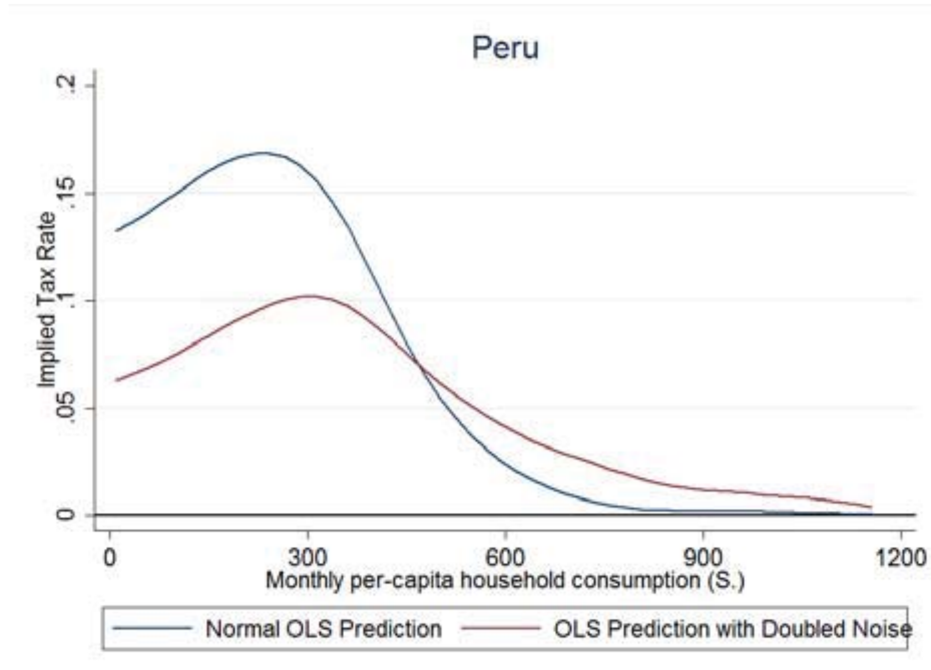
CRRA Utility - Indonesia
-4.60e-07
-4.80e-07
-5.00e-07
-5.20e-07
-5.40e-07
CRRA Utility - Peru
-.24
-.25
-.26
-.27
-.28
-.29
0
.2
.4
.6
.8
1 = UBI
Inclusion Error
Indonesia
Peru

Horizontal (in)equity



Implied tax rates





The form of transfers

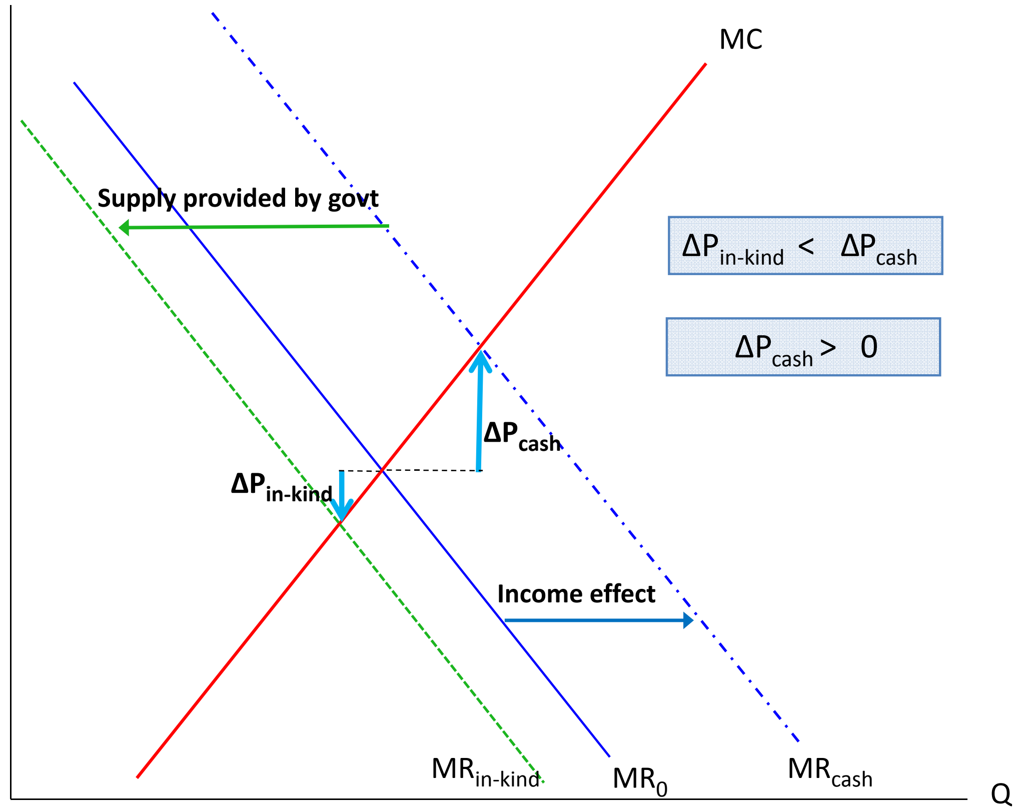
- Given that you've decided to do a transfer, what form should it take?
    - Cash vs. in-kind consumption goods vs. productive assets?
    - Conditional vs. unconditional transfers?
    - Large one-time transfer or smaller continual transfers?
    - Workfare vs cash?
- And how should you run the program?
    - Cash vs. electronic payments?
    - Smartcards, mobile phones, biometric identification?
    - Transparency about program benefits?
- Substantial research to date on point (1), only more recently on point (2)

Cash vs. in-kind

- What are the issues you might think about for cash vs in-kind?
- What would basic price theory say?
- Cash is a *demand* shock.In-kind is also a *supply* shock. How does this matter?
- Cunha, di Giorgi, and Jayachandran investigate one question: what happens to prices? And how does this affect the overall redistributive effects of the program?
- Examine an RCT where Mexican government randomized villages into receiving cash or food of equivalent value (flour, rice, beans, etc)
- How might this matter?

This is Econ 101...

Figure 1: Effect of cash and in-kind transfers on prices



Price effects

Table 6: Heterogeneous price effects based on remoteness of the village

	All PAL goods			Basic PAL goods only		
	Above-median remoteness	Below-median remoteness	All villages	Above-median remoteness	Below-median remoteness	All villages
Outcome =	price	price	price	price	price	price
	(1)	(2)	(3)	(4)	(5)	(6)
In-kind	-0.030	-0.044*	-0.050	-0.014	-0.045*	-0.033
	(0.033)	(0.024)	(0.030)	(0.027)	(0.027)	(0.031)
Cash	0.050	-0.029	0.013	0.062**	-0.015	0.032
	(0.034)	(0.031)	(0.031)	(0.031)	(0.038)	(0.036)
ln(Remoteness) x In-kind			-0.028			-0.007
			(0.033)			(0.036)
ln(Remoteness) x Cash			0.023			0.033
			(0.033)			(0.037)
Observations	865	1,470	2,130	603	1,014	1,471
***Effect size:* In-kind - Cash**	**-0.081*** **	**-0.015**		**-0.076*** **	**-0.030**	
***H_0:* In-kind = Cash (p-value)**	**0.00**	**0.56**		**0.00**	**0.35**	
***Effect size:* ln(Remoteness) x In-kind - ln(Remoteness) x Cash**			**-0.050** **			**-0.040***
***H_0:* ln(Remoteness) x In-kind = ln(Remoteness) x Cash (p-value)**			**0.02**			**0.08**

Consumption effects

- How would you think about consumption effects?
- How do the price effects matter? What else may matter?

Consumption effects

Table 5—Effects of Cash and In-Kind Transfers on Aggregated Consumption

Outcome = Consumption per capita of	Food plus nonfood (1)	All food items (2)	PAL food items (3)	Non-PAL food items (4)	Nonfood items (5)
In-kind	−31.28	−18.21	−1.30	−16.91	−13.07
	(28.49)	(16.28)	(2.46)	(14.96)	(13.65)
Cash	−12.53	−15.70	−0.16	−15.54	3.17
	(30.60)	(17.33)	(2.78)	(15.74)	(15.35)
Post	196.05***	83.93***	7.35***	76.58***	112.12***
	(27.54)	(16.91)	(2.15)	(15.68)	(12.96)
In-kind × *Post*	50.69*	41.63**	44.05***	−2.43	9.06
	(28.44)	(17.62)	(4.07)	(15.79)	(13.64)
Cash × *Post*	36.09	24.35	5.98*	18.38	11.73
	(32.69)	(20.47)	(3.06)	(18.67)	(16.46)
Observations	10,985	10,985	10,985	10,985	10,985
Differential effect: *In-kind* × *Post* − *Cash* × *Post*	14.60	17.27	38.08***	−20.80	−2.67
H_0: *In-kind* × *Post* = *Cash* × *Post*, *p*-value	0.55	0.26	0.00	0.13	0.84
Equal valued transfer: $(Cash \times Post)^{EQ}$	48.86	32.97	8.09*	24.88	15.89
	(44.26)	(27.71)	(4.14)	(25.28)	(22.29)
Differential effect: *In-kind* × *Post* − $(Cash \times Post)^{EQ}$	1.83	8.65	35.96***	−27.31	−6.82
H_0: *In-kind* × *Post* = $(Cash \times Post)^{EQ}$, *p*-value	0.95	0.67	0.00	0.13	0.69

Consumption effects

Table 7—Effects of Cash and In-Kind Transfers on Disaggregated Consumption Categories

Consumption per capita	*In-kind* × *Post* (1)	(s.e.) (2)	(*Cash* × *Post*)^{EQ} (3)	(s.e.) (4)	(1)=(3) *p*-value (5)
Fruits and vegetables	9.00**	(3.80)	15.40**	(6.34)	0.19
All grains and pulses	16.28***	(3.69)	8.26	(5.83)	0.12
Corn our †	2.30***	(0.66)	−0.20	(0.91)	0.00***
Corn kernels and tortillas	−0.22	(2.01)	3.94	(3.70)	0.21
Rice †	0.49	(0.33)	−0.69	(0.49)	0.00***
Pasta †	1.55***	(0.32)	−0.26	(0.46)	0.00***
Biscuits †	6.36***	(0.90)	3.72***	(1.12)	0.01**
Cereal †	3.96***	(0.80)	0.26	(0.77)	0.00***
Beans †	−0.11	(0.72)	−0.01	(1.00)	0.89
Lentils †	1.88***	(0.21)	0.07	(0.22)	0.00***
All dairy and animal products	13.70*	(7.85)	7.93	(12.16)	0.52
Milk powder †	23.37***	(2.32)	4.59***	(1.38)	0.00***
Liquid milk	−12.57***	(2.62)	−2.29	(4.04)	0.00***
Cheese and yogurt	0.19	(1.41)	0.84	(2.25)	0.69
Chicken	−1.54	(2.01)	−0.74	(3.15)	0.77
Beef and pork	2.04	(1.57)	2.27	(2.44)	0.90
Seafood	−0.09	(1.82)	3.71	(3.46)	0.20
Canned fish†	4.29***	(0.63)	1.32	(0.81)	0.00***
All fats	0.28	(0.73)	0.20	(1.17)	0.92
Vegetable oil †	0.61	(0.56)	−0.59	(0.80)	0.03**
Lard and mayonnaise	−0.30	(0.36)	0.79	(0.63)	0.04**
Vices					
Junk food and sweet drinks	1.90	(3.09)	1.87	(4.66)	0.99
Alcohol	0.11	(1.46)	0.83	(2.12)	0.66
Tobacco	−0.43	(0.50)	−1.55*	(0.78)	0.05*
Nonfood					
Education related expenses	2.66	(3.53)	6.07	(5.75)	0.45
Medicine and hygiene products	4.59	(5.01)	8.67	(9.48)	0.61
Transportation	1.45	(4.97)	2.07	(7.90)	0.91
Clothing	−1.45	(1.89)	−1.09	(2.87)	0.87
Household items	1.76	(4.66)	1.52	(7.25)	0.96

Consumption effects

TABLE 8—EFFECTS OF CASH AND IN-KIND TRANSFERS ON CHILDREN'S CALORIC AND NUTRITIONAL INTAKE

	Calories	Vitamin C (mg)	Iron (mg)	Zinc (mg)	Calories > RDA	Vitamin C > RDA	Iron > RDA	Zinc > RDA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-kind × *Post*	89.92**	22.81***	1.28***	1.18***	0.06**	0.21***	0.11***	0.11**
	(39.98)	(5.08)	(0.43)	(0.32)	(0.03)	(0.04)	(0.04)	(0.05)
$(Cash \times Post)^{EQ}$	21.85	23.77**	0.64	0.84*				
	(67.68)	(10.20)	(0.68)	(0.46)				
Cash × *Post*					0.04	0.09	0.00	0.03
					(0.03)	(0.05)	(0.04)	(0.06)
Observations	4,031	4,031	4,031	4,031	4,031	4,031	4,031	4,031
H_0: *In-kind* × *Post* = $(Cash \times Post)^{EQ}$, *p*-value	0.21	0.92	0.26	0.35				
H_0: *In-kind* × *Post* = *Cash* × *Post*, *p*-value					0.35	0.02**	0.00***	0.08*

Condition or not?

Baird, McIntosh, and Özler (2011): Cash or Condition?

- Conditional cash transfers condition aid on fulfilling a set of criteria that the government thinks are good
- E.g., sending your kids to school, getting kids immunized, etc
- Justification for paternalism here is intergenerational: if parents don't fully internalize value to kids of human capital acquisition, government can correct this by incentivizing this behavior
- How should we think about this?
- Two effects:
  - Decreases the 'price' of human capital acquisition (price effect). Changes this behavior those households on the margin of doing this or not.
  - But, for households who are far from the margin, they may get cut off from the transfer (negative income effect).

Some caveats

- Many RCTs of CCT programs. But before this paper all were CCT vs nothing. This conflates the overall income effect of CCT with the particular effects of conditioning here
- Conditioning may also be a signal to parents of what they are supposed to do. This is a 'labeling' effect. Benhassine et al (2014) find evidence of this.

TABLE III

PROGRAM IMPACT ON SCHOOL ENROLLMENT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Program impacts on *self-reported* school enrollment								
	Dependent variable: =1 if enrolled in school during the relevant term							
	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
	(0.011)	(0.011)	(0.017)	(0.017)	(0.018)	(0.019)	(0.070)	(0.025)
Unconditional treatment	0.034***	0.051***	0.054***	0.072***	0.095***	0.101***	0.406***	0.074***
	(0.010)	(0.011)	(0.018)	(0.021)	(0.022)	(0.021)	(0.079)	(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-reported* school enrollment								
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
Prob > F(Conditional = Unconditional)	0.173	0.732	0.067	0.076	0.014	0.020	0.011	0.108

Results

Test scores

TABLE VI

PROGRAM IMPACTS ON TEST SCORES

	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^{***}
	(0.054)	(0.067)	(0.057)	(0.048)
Unconditional treatment	-0.030	0.006	0.063	0.136
	(0.084)	(0.098)	(0.087)	(0.119)
Number of observations	2,057	2,057	2,057	2,057
Prob $> F$(Conditional= Unconditional)	0.069	0.276	0.797	0.756

Results

Marriage and enrollment

TABLE VIII

PREVALENCE OF BEING EVER MARRIED BY SCHOOL ENROLLMENT STATUS DURING TERM 1, 2010

	(1) Enrolled	(2) Not enrolled	(3) 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)

Results

Marriage and enrollment

TABLE IX

TEACHER-REPORTED SCHOOL ENROLLMENT AND MARITAL STATUS IN ROUND 3

	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

Next steps: implementation

- More recent research is on the implementation of these programs
  - Can transparency reduce corruption? Paper in Indonesia says yes.
  - Can technology reduce corruption? Paper in India on smart-cards.
  - In fact, even changing back-end payment systems can reduce corruption.
  - What about outsourcing distribution? Competition? Paper in Indonesia on this.

The next frontier

- Many developing countries are now trying to expand social safety nets to cover other things: health insurance, disability insurance, etc
- How can governments deal with these programs in a low-information environment?

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