14.771: Public Finance Lecture

Ben Olken

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

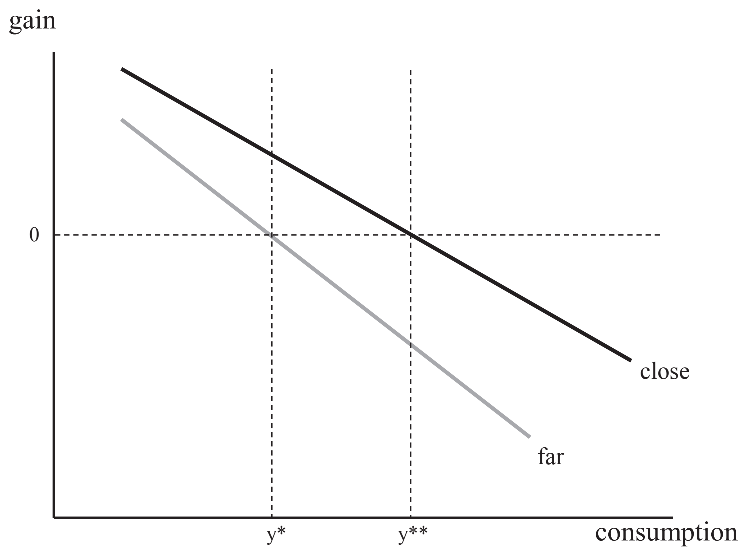
Self-Targeting

- 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

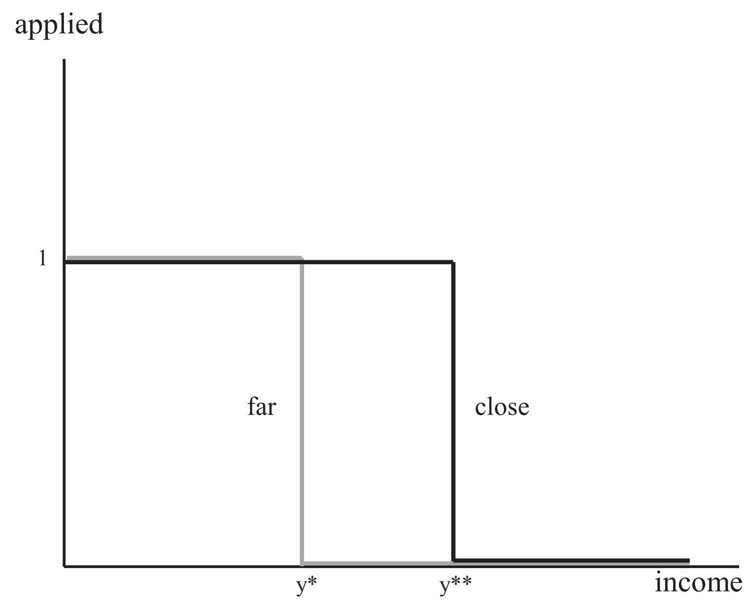
Simple self-targeting model

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

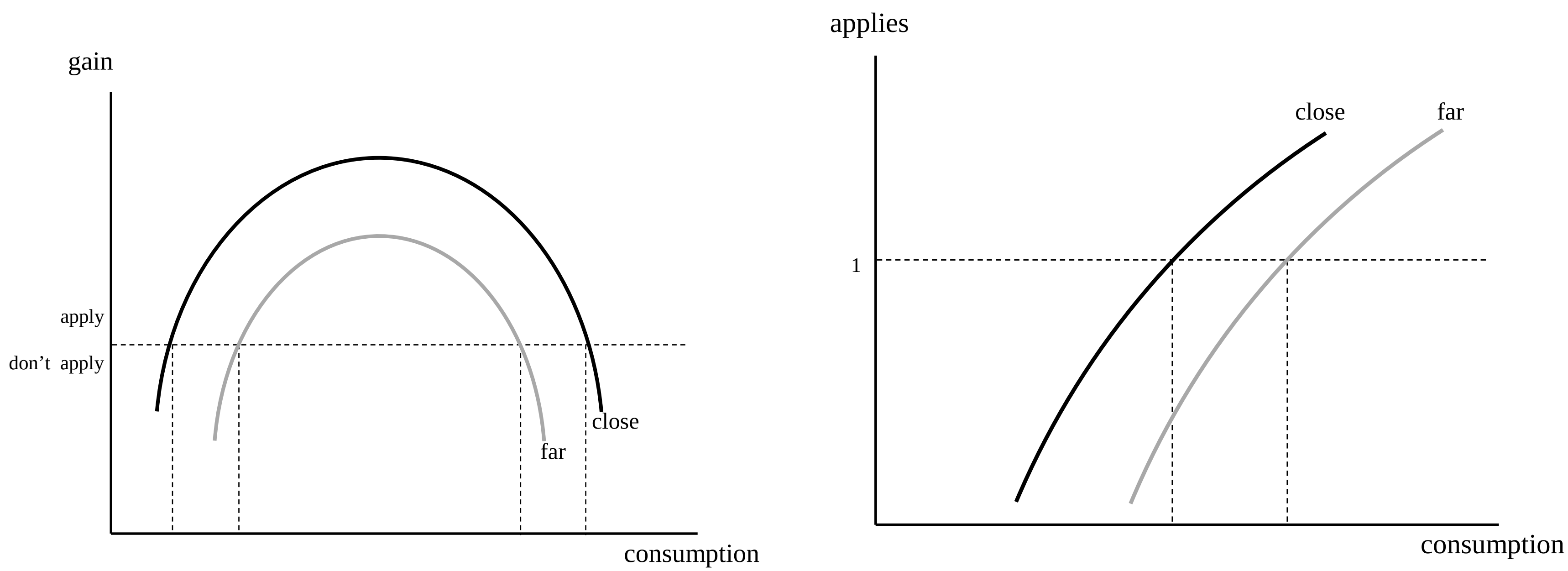
Self-Targeting Theory

- 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



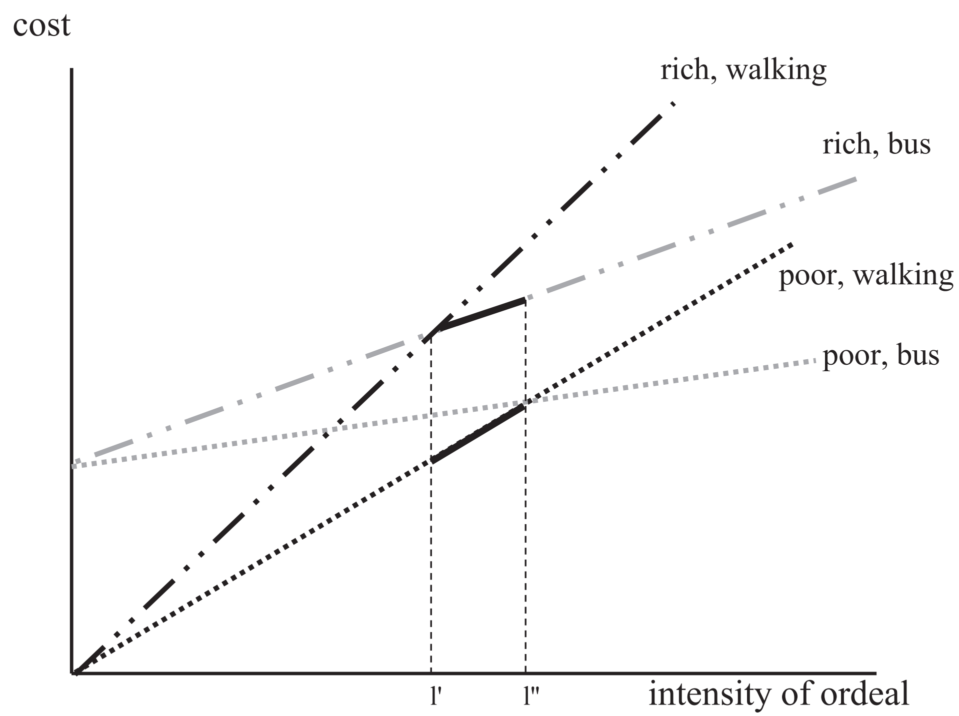
(A) Gain vs. consumption for close and far subtreatments

(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

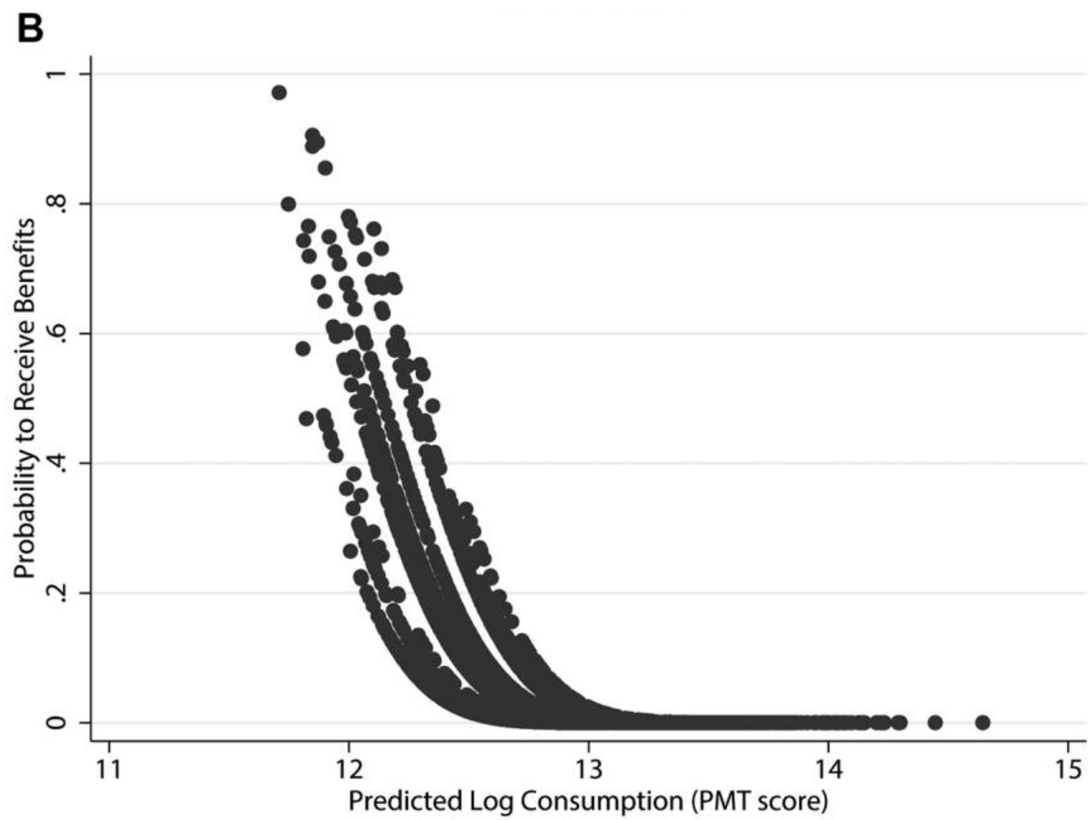


Applying this to a targeting program

- 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 $X'\beta$.

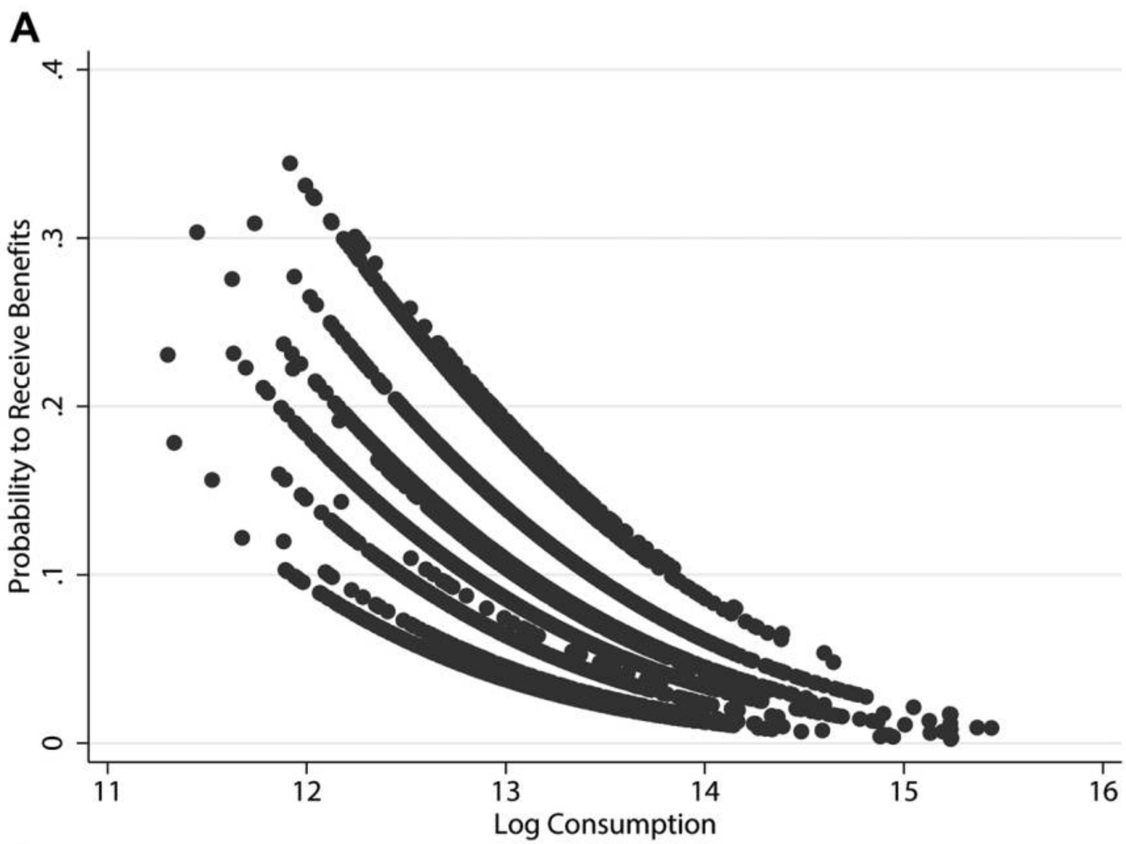
Success rates conditional on applying

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:

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

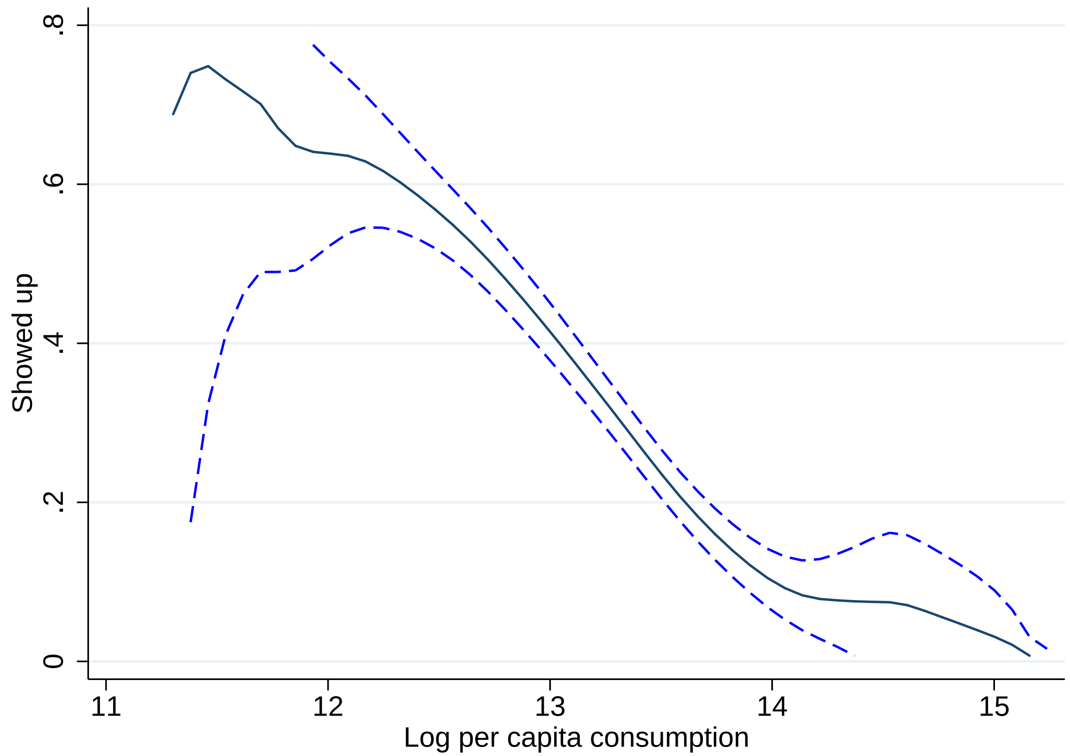
- Denote by α the share of sophisticated households
- To close the model need to assume that the $\lambda(y)$ function is correct given the underlying PMT process μ and the composition of who applies in equilibrium

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

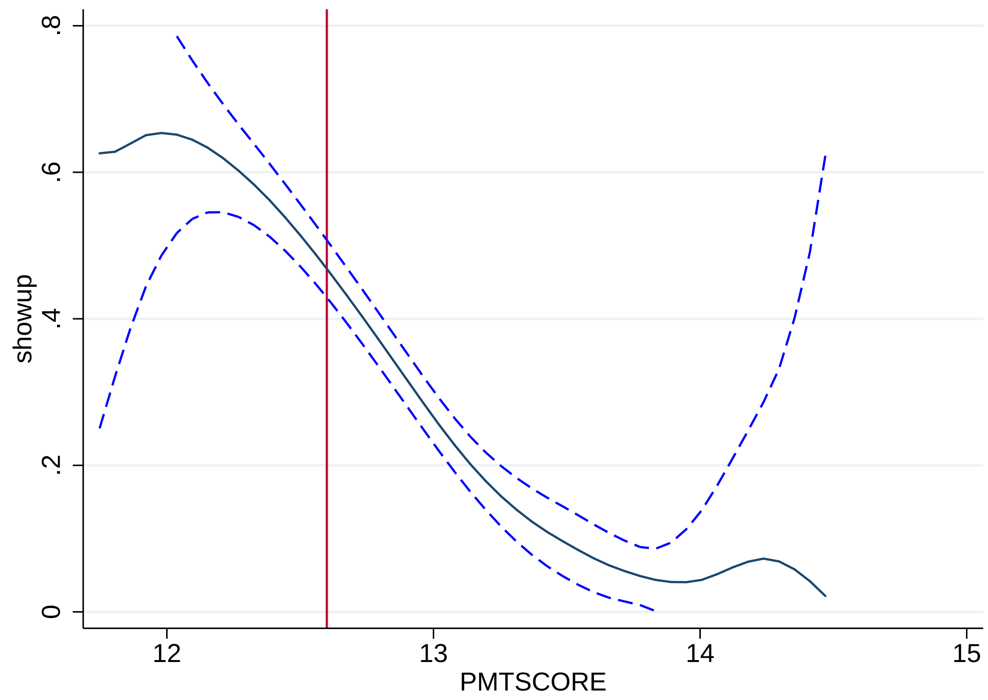
Figure 5. Showup Rates Versus Log Per Capita Consumption



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

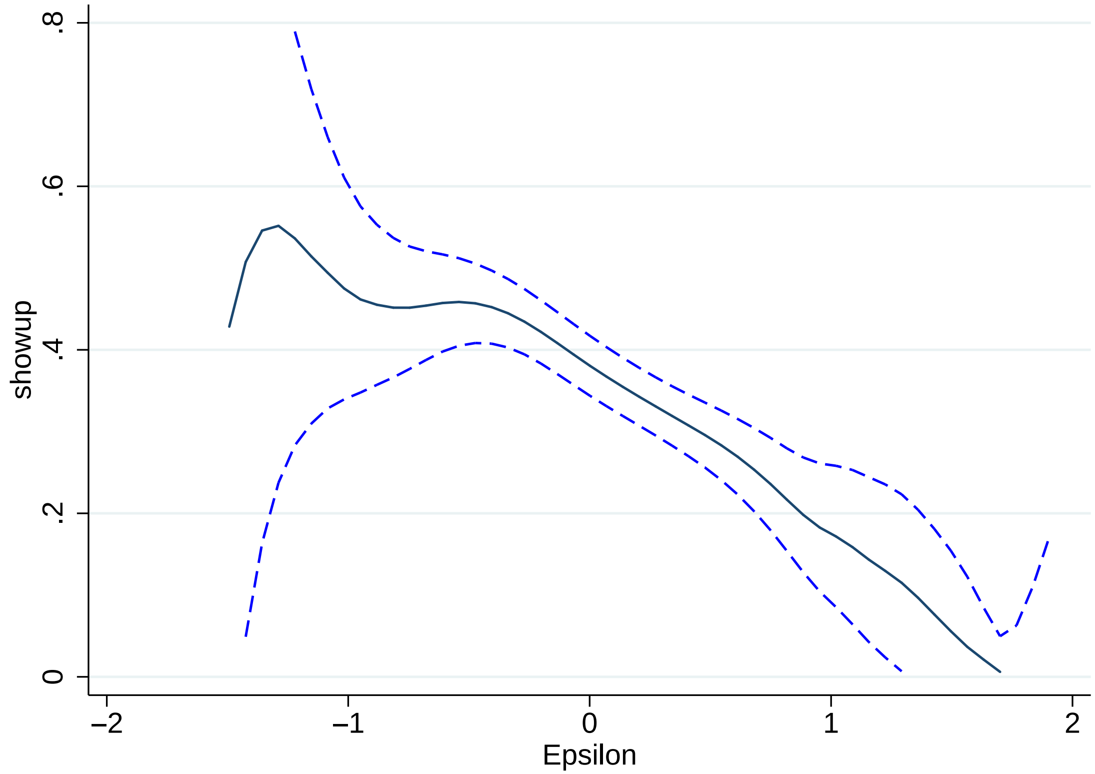
On observables...

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)

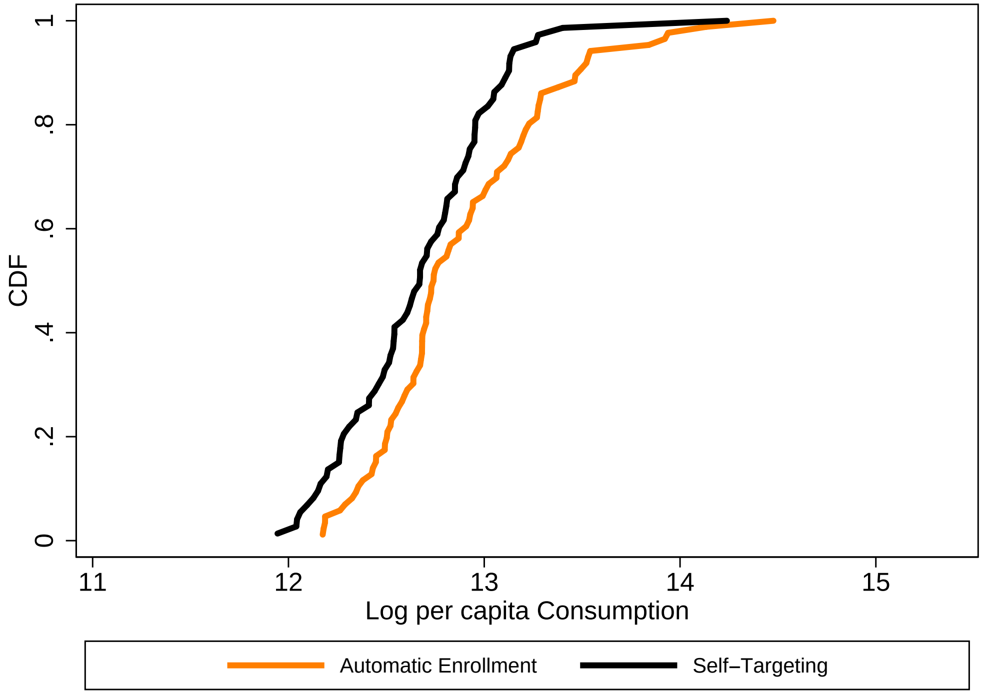
Selection on both observables and unobservables

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

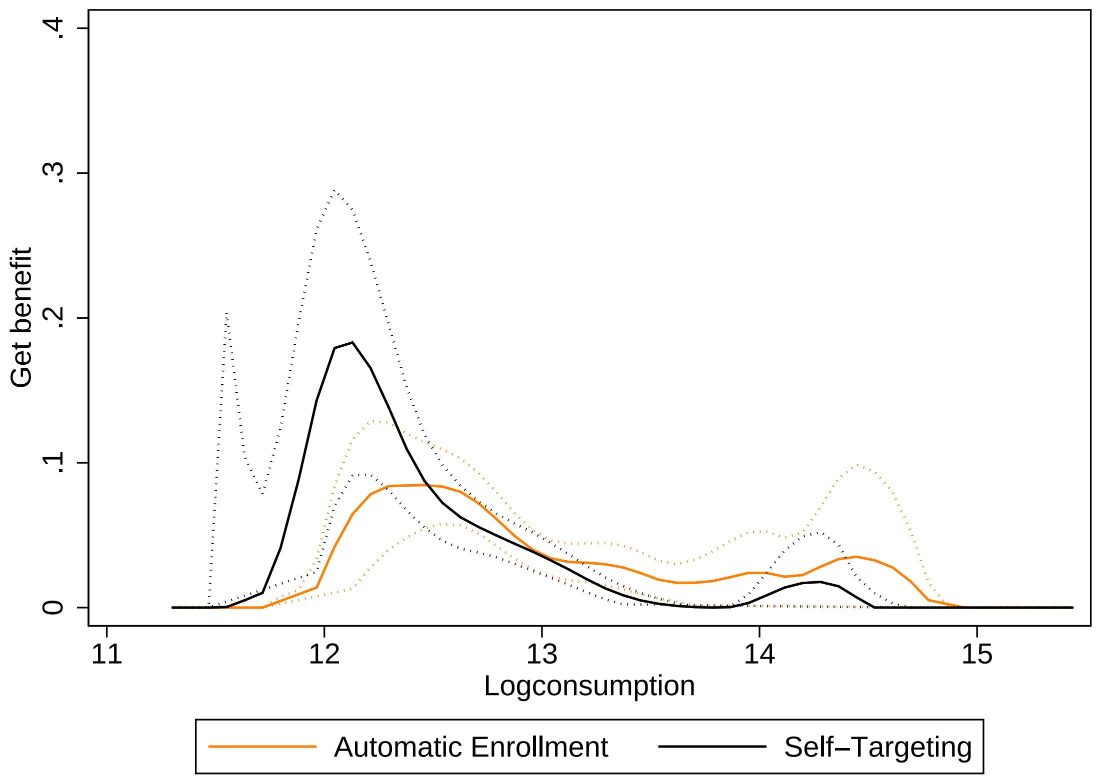
Comparison to actual (pre-selected) PMT...

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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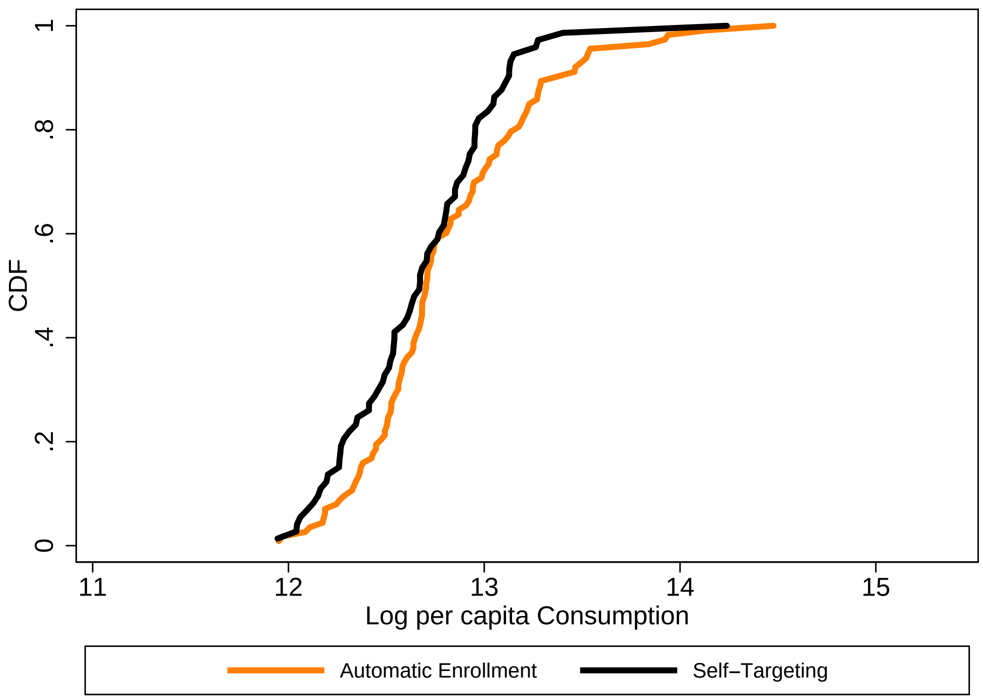
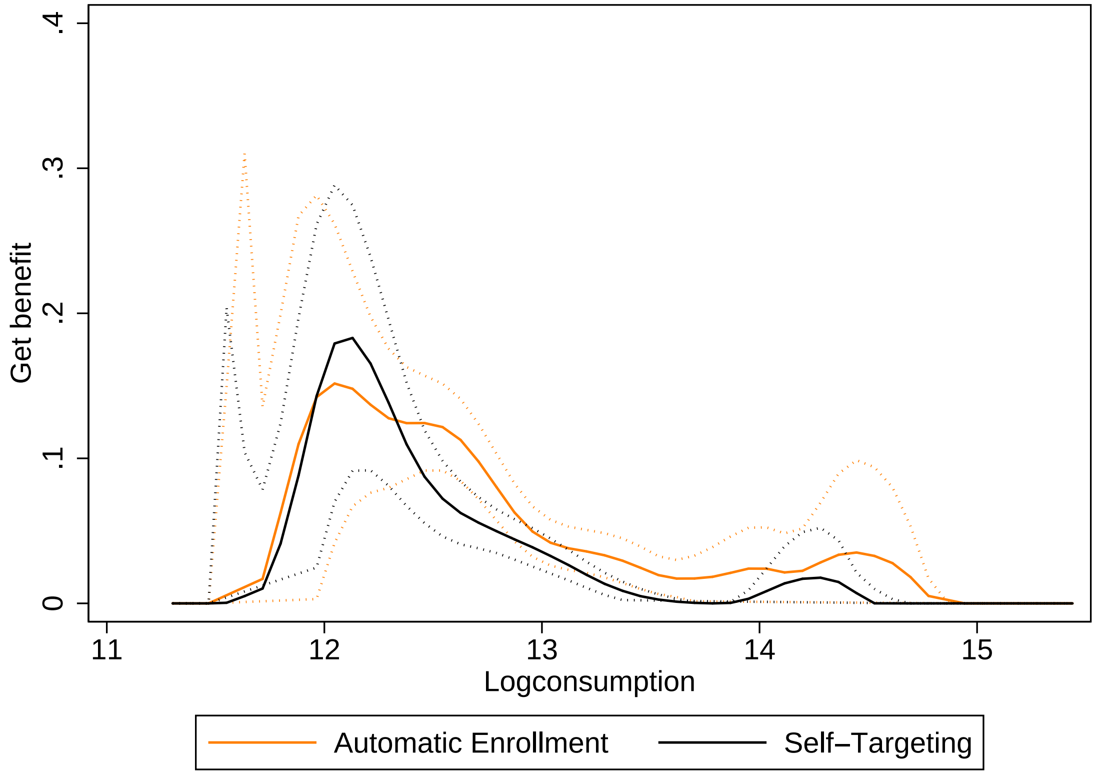
Comparison to hypothetical universal PMT...

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 $c(y_i, l_i) = wage_i * \left(traveltime_i + \overline{waittime}\right) + travelmoney_i$, 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)	redicted 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

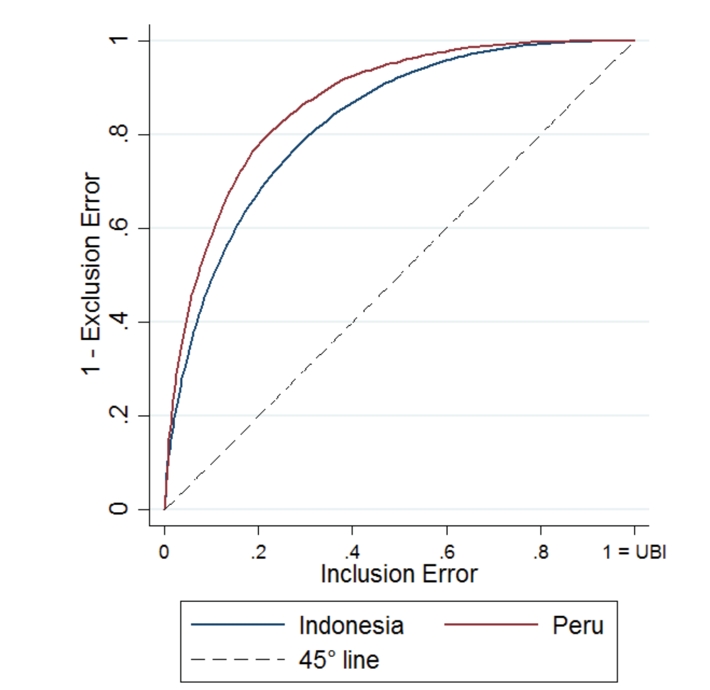
$$U = \frac{\sum (y_i + b_i)^{1-\rho}}{1-\rho}$$

- 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

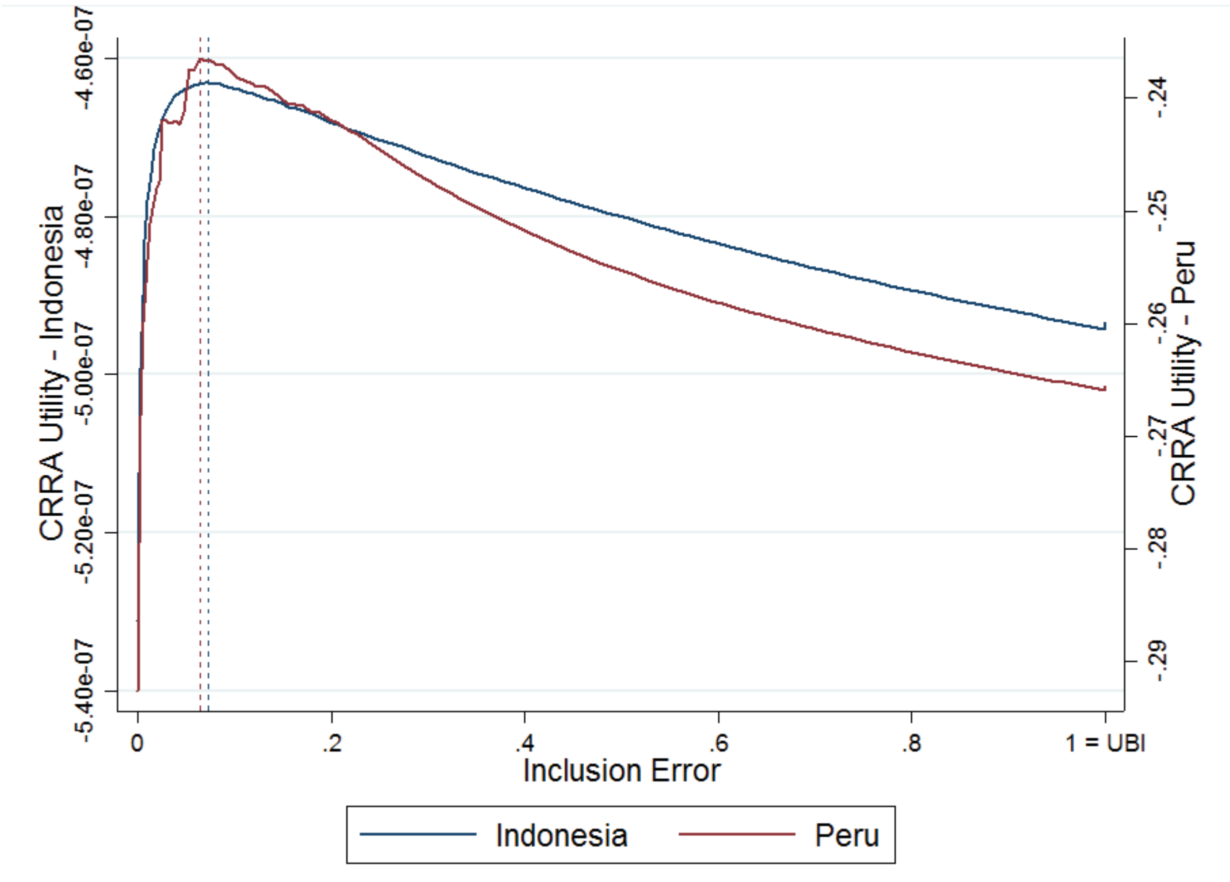
Figure 4: Tradeoffs between inclusion error and exclusion error by varying eligibility cutoff

Panel A: ROC Curves for Program Targeting



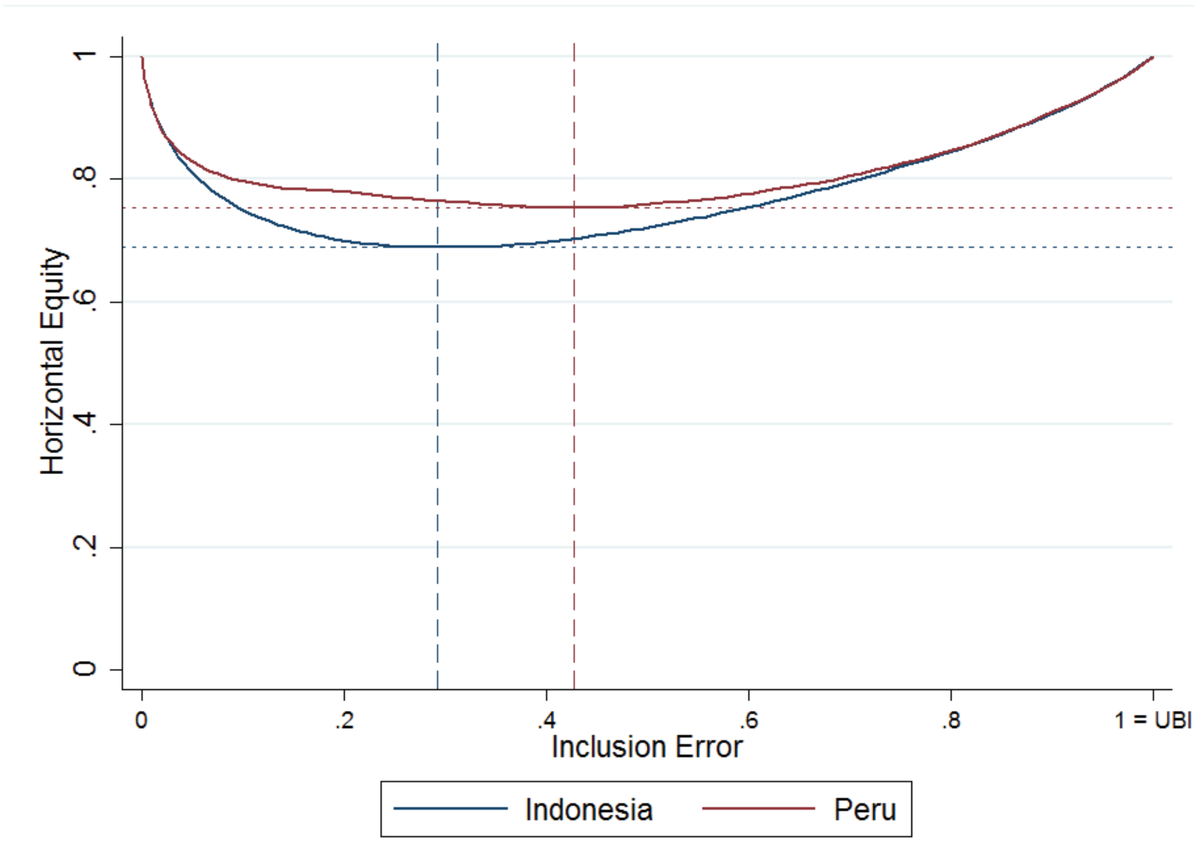
- Aside: this is an ROC curve. What is this?

Welfare

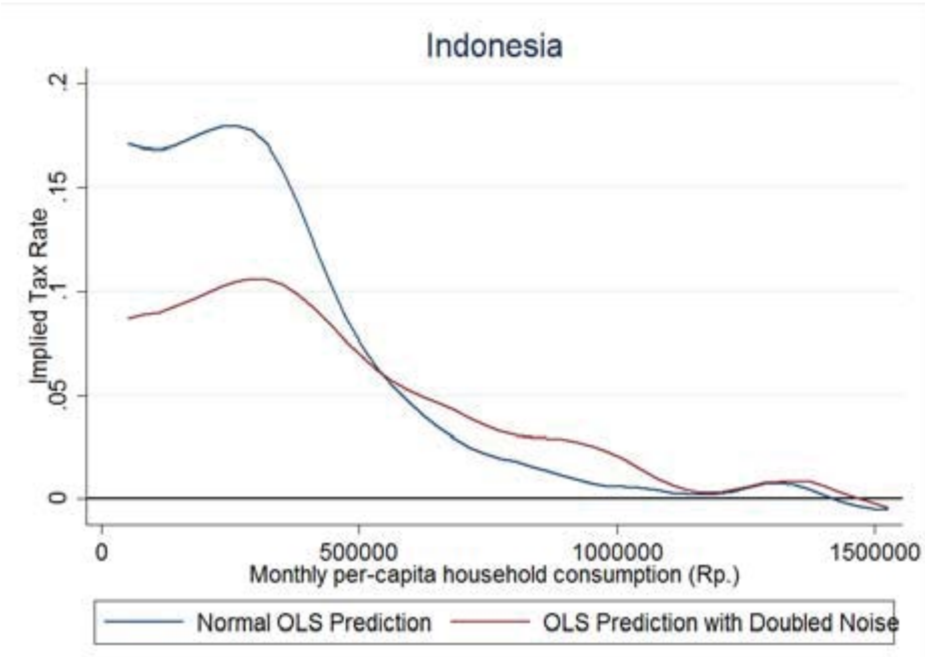


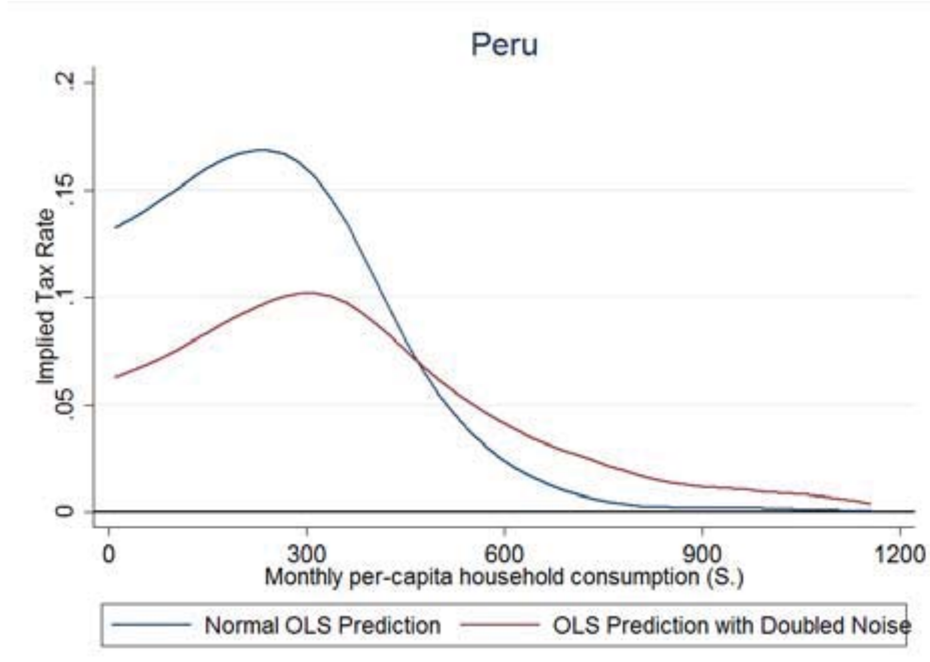
-4.60e-07
-4.80e-07
-5.00e-07
-5.20e-07
-5.40e-07
CRRA Utility - Indonesia
-.24
-.25
-.26
-.27
-.28
-.29
CRRA Utility - Peru
0
.2
.4
.6
.8
1 = UBI
Inclusion Error
Indonesia
Peru

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?

14.771: Development Economics
Fall 2021