# The Challenges of Social Protection in the Developing World

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NBER DEV Master Lecture Series

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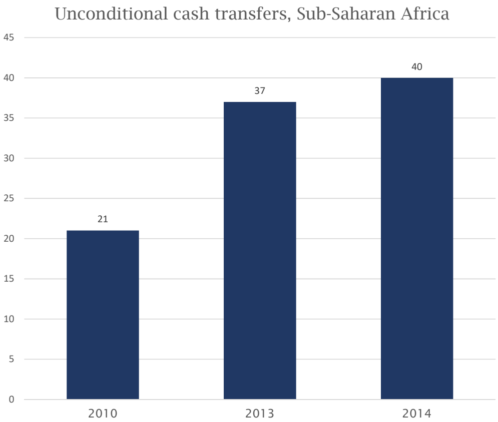
# Social assistance spending rises as countries develop


Source: Social insurance data from ILO.

# But programs in many developing countries programs, and growing rapidly



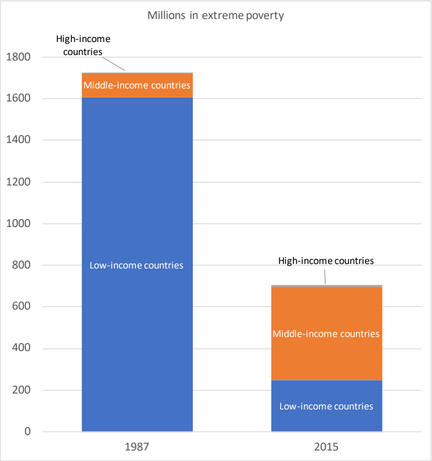


Source: World Bank State of Social Safety Nets

# Part of this reflects economic growth

- As many low-income countries become middle income:
  - Tax capacity tends to increase
  - But inequality means that there are many extreme poor in these countries
- There is thus substantial scope for within-country redistribution to help alleviate extreme poverty
- In fact, most of the extreme poor live now live in middle income countries (Pande and Page 2018)

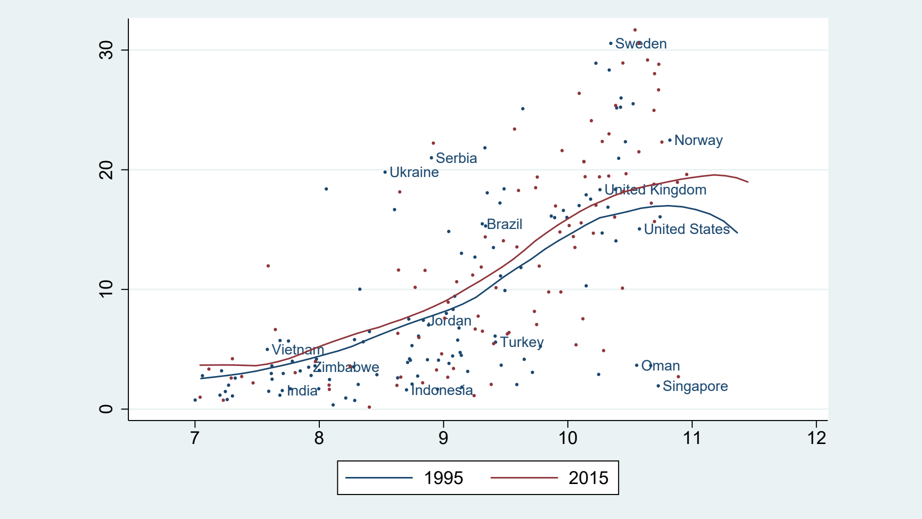
# Most extreme poor now live in middle-income countries




Source: Page and Pande 2018.

- This change reflects India, China, Indonesia, Nigeria, and Pakistan all becoming middle income - while still retaining some non-trivial amount of extreme poverty

# Expansion in social assistance not just driven by economic growth

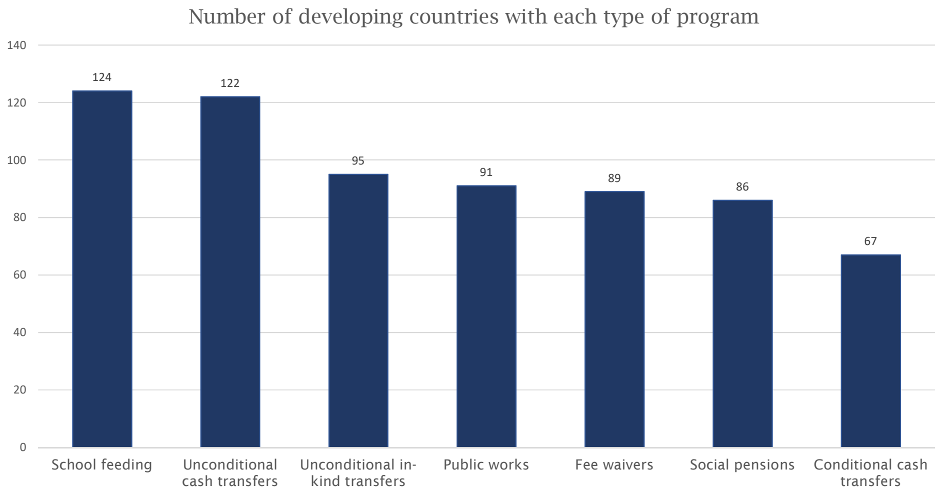



Source: Social insurance data from ILO.

# These programs encompass a wide range of goals

- Smoothing temporary shocks (and filling holes in private insurance markets)
  - Idiosyncratic shocks
  - Aggregate shocks
- Redistribution for the permanent component of income
- Breaking poverty traps
  - Within generation
  - Intergenerational
- Smoothing over the lifecycle (e.g., pensions)

# With a wide variety of programs




Source: World Bank State of Social Safety Nets

# What makes social protection a development economics problem?

- All this suggests we should expect to see more of a wide range of safety nets and social insurance programs in developing countries
- But, what is distinctive in developing countries about this problem?
- I will focus on three distinct challenges:
- *Targeting challenge*: how to identify beneficiaries in a low information environment
- *Program design challenge*: different forms of transfers and program design may be most appropriate with extreme poverty, large informal sector, high participation in subsistence agriculture, etc.
- *Governance challenge*: how ensuring assistance is delivered with low leakage

# A word of thanks

- Special thanks to my many co-authors and collaborators
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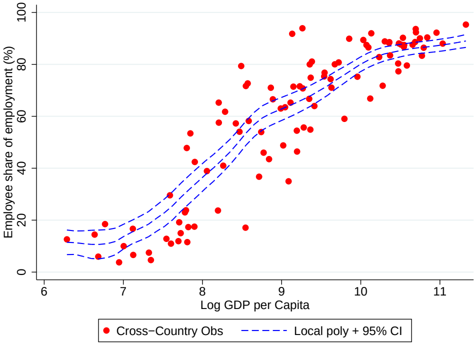
# Targeting

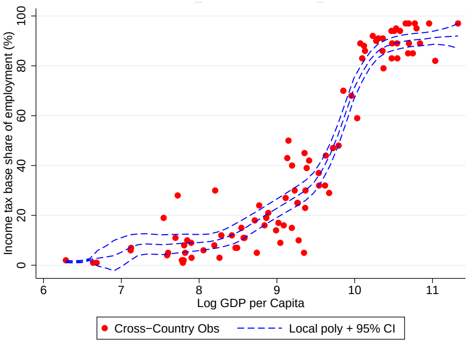
# Targeting

- For many types of programs (e.g. redistribution, poverty traps, etc.), we'd like to target programs to the poor.
- 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:
  - Pervasive self and informal employment means most people's income isn't third-party reported, and hence is excluded from tax net reported (Jensen 2019)

# Income taxes exclude most poor and near-poor




Employee Share




Share non-Exempt from Income Tax

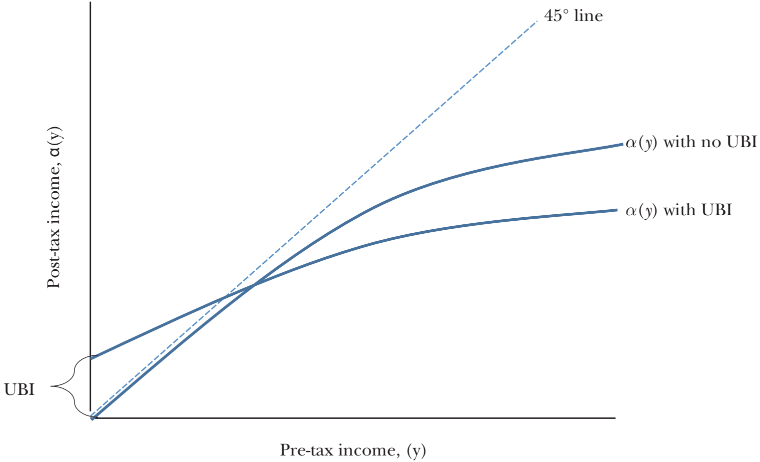
Source: Jensen (2019)

# Implications

- Limits use of the tax code for redistribution → many targeting tools from US won't work (so, no income-based means testing, no EITC, etc.)
- Implies universal programs are substantially more costly relative to targeted programs (Hanna and Olken 2018)

# UBIs in developed countries

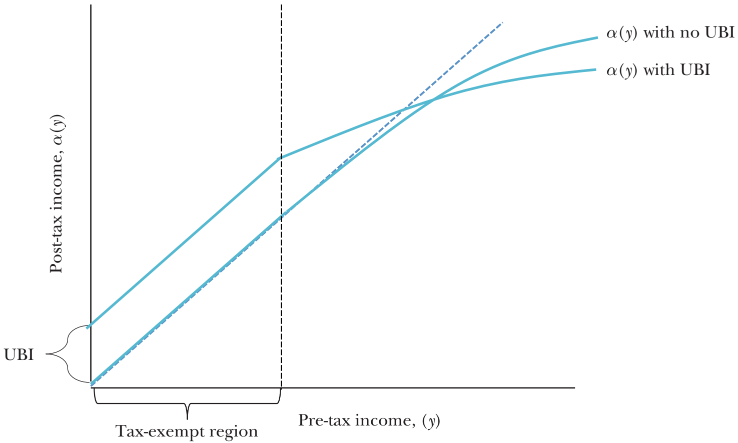
**Example of Progressive Post-Tax Income Schedules With and Without a Universal Basic Income (UBI)**




Source: Hanna and Olken (2018)

# UBIs in a developing country

**Example of Post-Tax Income Schedules With and Without a Universal Basic Income (UBI), with a Tax-Exempt Region**




Source: Hanna and Olken (2018)

# Targeting

- Suppose you want to differentiate among the poor (in the tax-exempt region).
- Explicit targeting
  - Proxy-means tests: target based on $\hat{y}$, predicted based on assets
  - Community-based targeting: local input
  - Geographic targeting: collect $y_r$ for each regional $r$, use that
- Choice-based targeting
  - Ordeal mechanisms: add a cost that screens out the rich
  - Price-based subsidies: change $p$ for certain goods preferred by the poor

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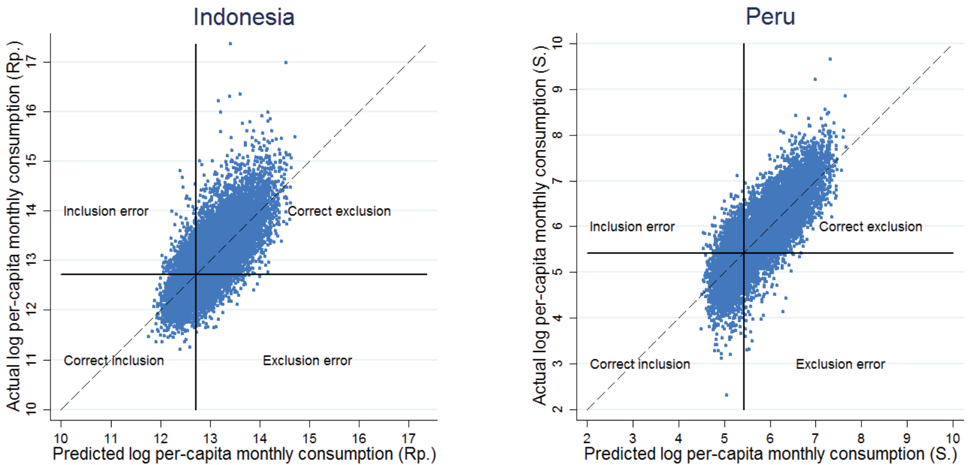
  - Ordeal mechanisms: *impose costs on the poor; may not screen if poor dissuaded by costs*
  - Price-based subsidies: *hard to find these goods; in practice often political economy means subsidize goods used by middle class; distorts consumption*
- Suggests a need for some empirical evidence on tradeoffs

# Proxy-means tests are imperfect

## Examples of PMT prediction errors




Source: Hanna and Olken (2018)

# Proxy-means tests vs. other explicit approaches

## Testing PMT vs. Community Approach

- Can community-based targeting improve upon PMT?
- Alderman (2002): Local communities have some information beyond PMT
- Bardhan and Mookherjee (2000, 2005): This may not actually be helpful
- Alatas et al (2012): What happens in practice when we try to use local information for targeting?
  - Randomized trial
  - Step 1: Baseline survey to measure the 'truth' (more on this in a minute)
  - Step 2: Randomize villages to target one-time transfer based on PMT, community approach, or a hybrid

# Community-based targeting in practice

## Alatas et al (2012)

# Community-based targeting in practice

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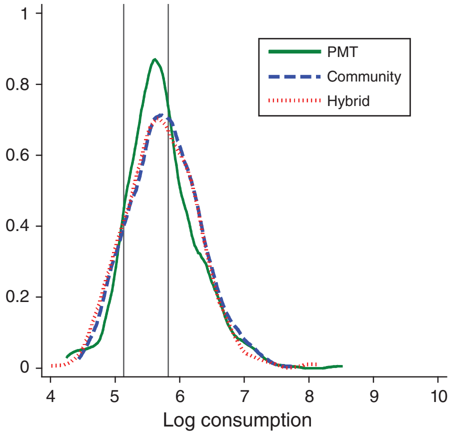
# PMT does a better job based on per-capita consumption




Source: Alatas et al (2012)

- PMT centered to the left of community methods
- Note community methods select slightly of the very poor (those below PPP $1 per day)

# But community targeting does a better job matching 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 |

Source: Alatas et al (2012)

# And people seem to be much happier with community results

| | 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) |
|---|---|---|---|---|---|
| Community treatment | 0.161*** | 0.245*** | −0.189*** | −0.578*** | −0.554*** |
| | (0.056) | (0.049) | (0.040) | (0.158) | (0.112) |
| Hybrid treatment | 0.018 | 0.063 | 0.020 | 0.078 | −0.171 |
| | (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 |

Source: Alatas et al (2012)

# Choice based 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
- Large ordeals
  - Problem with this is that it imposes a negative, socially inefficient cost on beneficiaries
  - Most prominent example: NREGA and related schemes in India (see, e.g., Murgai, Ravallion, and van de Walle 2015)
- Small ordeals
  - Alatas et al (2016): on-demand application
  - Dupas et al (2018): vouchers instead of free delivery for chlorine

# On-demand application as an ordeal

## Alatas et al 2016: "Evidence from a Field Experiment in Indonesia"

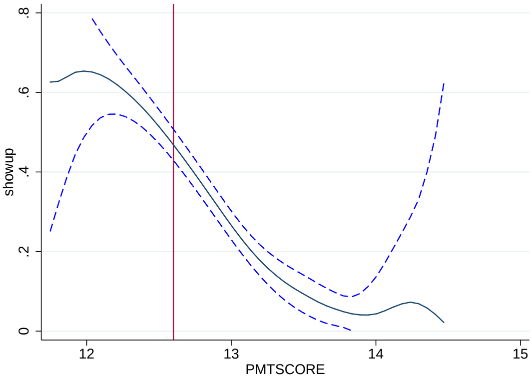
- Key idea
  - Require households to pay a small cost to apply for benefits
  - Households know their true income, but not the part the government observes
  - So the decision to apply for benefits reveals information to the government
- Model
  - Decompose income into $y = y^o + y^u$, where $y^o$ is the part the government can observe through PMT and $y^u$ is the residual
  - Define $\mu(y^o)$ to be the probability you pass the PMT as a function of observable income and $\lambda(y)$ to be the probability you pass the PMT as a function of your total income
  - Define $c$ as cost of applying and $b$ as benefit
  - A households will apply if

$$-c + \lambda(y)(b) > 0$$

  - This helps because households with low $y^o$ but high $y^u$ do not bother to apply
- Tested this idea in a separate, high-stakes RCT (CCT valued at \$150/year for 6 years)

# Applications vs. observable income

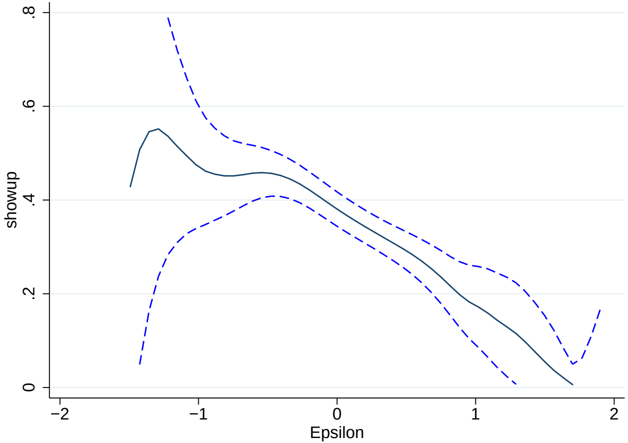
FIGURE 6. Showup Rates Versus Observable and Unobservable Components of Log Per Capita Consumption




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

Source: Alatas et al (2016)

# Applications vs. unobservable income



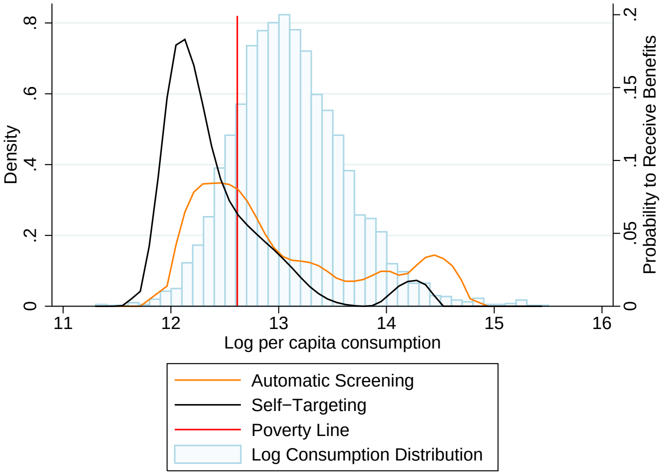

(B) Showup as a function of unobservable consumption ($\varepsilon_i$)



Source: Alatas et al (2016)

# Comparison to actual (pre-selected) PMT

## Probability of getting benefits




Source: Alatas et al (2016)

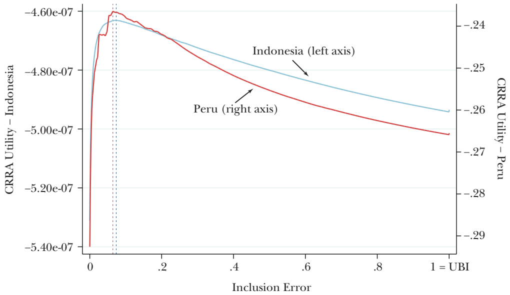
# Should we bother targeting at all?

- What should be clear from all of this: for all these methods, targeting is imperfect
- So a current debate says: should we give up, and make benefits universal?
  - This is still redistributive (imagine tax proportional to income and rebated lump sum)
  - Eliminates exclusion error and horizontal inequity (by construction)
  - May be more politically salient
  - But per-beneficiary, you get much smaller transfer than a targeted program
- How to think about this?
  - Hanna and Olken (2018) run a simple welfare calculation using data from Indonesia and Peru
  - Assume CRRA utility, so

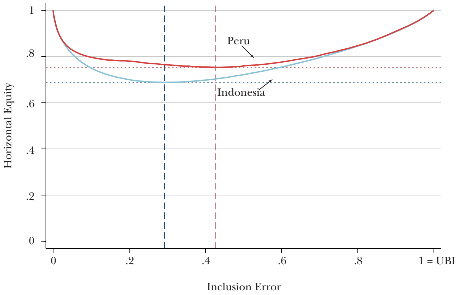
$$U = \frac{\sum (y_i + b_i)^{1-\rho}}{1-\rho}$$

  - 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 with different thresholds (including no targeting)
  - Can also calculate horizontal inequality (fraction of people with income similar to you who get something different)

# Welfare vs. horizontal inequality




Welfare




Horizontal equity

Source: Hanna and Olken (2018)

# Does targeting create distortions?

- Another argument against targeting: maybe it creates distortions?
  - E.g. the 18th century window tax in England and Scotland led to dark houses (Oates and Schwab 2015)
- How to think about this in a modern context?
- Banerjee et al (2018): nationwide RCT in Indonesia
  - Randomized several new questions (TVs, cell phones) onto the national poverty census by province
  - Find small decline in reported TVs in subsequent government data, but disappears 1 year later
  - And no change in actual TV or cell phones sales

# Program Design

# What form should programs take?

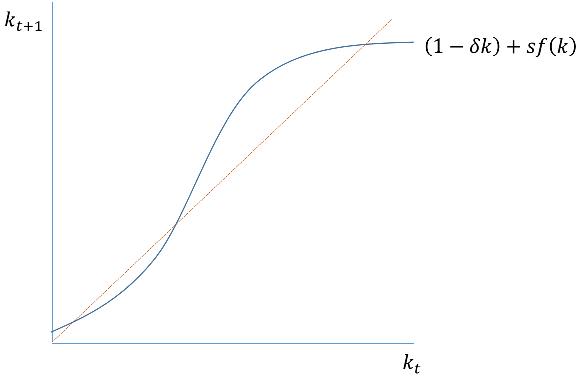
- What form should transfers take?
- Benchmark: stream of unconditional cash payments
- But many other alternatives:
  - Conditional cash transfers
  - In-kind transfers (food, housing, etc.)
  - Lumpy cash transfers or asset transfers
  - Price subsidies (e.g. subsidized fuel, housing)
  - Social insurance programs (e.g. health insurance, unemployment insurance)
  - Pensions (age-restricted transfers)
- And many other design decisions. For example:
  - How long are transfers guaranteed?
  - Who in the household should the recipient be?
  - Should these be bundled or separate?
- These policy options are available everywhere

# What is distinctive about development here?

- Poverty traps:
    - Extreme poverty plus savings constraints may create poverty traps. $\rightarrow$ May be a role for lumpy transfers rather than stream of payments.
    - Low levels of basic human capital (health / education) suggest intergenerational mobility may be lower in developing countries, particularly for disadvantaged groups (Asher, Novosad, and Rafkin 2018). $\rightarrow$ Rationale for CCTs.
- Rural and poorly integrated markets
    - Price effects of in-kind vs. cash transfers. E.g., Cunha, de Giorgi, and Jayachandran (2019)
    - Local spillover effects. E.g., Muralidharan, Niehaus, and Sukhtankar (2018)
    - Substantial agricultural risk. E.g., Adhvaryu et al (2019)
- Substantial informal economy
    - Challenges for UI, workers comp, and other labor market programs
- Challenges in distribution
- Substantial evidence on many of these programs and many of these questions. But let me focus on poverty traps.

# Poverty traps

- Poverty traps + savings constraints suggest a large, lumpy transfer could have larger effects than an equivalent stream of small transfers, by enabling investments.




- Is this true?

# Lumpy Cash Transfers

- Give Directly Experiment (Haushofer and Shapiro 2016; 2018) randomized lump-sum transfers vs. payment in 9 monthly installments
  - At 9 months, some evidence that monthly transfers increased food security, whereas lumpy transfers increased assets (predominantly: metal roofs)
  - At 3 years, no difference between lump-sum and monthly transfers
  - While lump-sum large in magnitude, monthly payments only spread over 9 months - may understate difference compared to a steady-state transfer program

- Barrera-Osorio et al (2011, 2019) - lump-sum CCT transfers in Columbia
  - Modifying a CCT so that $\frac{1}{3}$ of payments are made in a lump sum, at time of next school enrollment, increases secondary and long-run tertiary enrollment relative to stream of payments

# Lumpy Asset Transfers

- Many authors have evaluated the "Targeting the Ultra-Poor" programs
  - Pioneered by BRAC; replicated in 20+ countries
  - Generally consists of a lumpy productive asset (usually livestock), bundled with regular cash payments for some period (about a year), skills training, savings, some health education, regular visits for coaching
- Studies
  - 3-4years (1-2 years after program ends): Bandiera et al (2017) in Bangladesh; Banerjee et al (2015) in Ethiopia, Ghana, Honduras, India, Pakistan, and Peru; Bedoya et al (2019) in Afghanistan
  - 7 years (5 years after program ends): Bandiera et al (2017) in Bangladesh; Banerjee et al (2016) in West Bengal

# Lumpy Asset Transfers

| | (1) Total per capita consumption, standardized | (2) Food security index | (3) Asset index | (4) Financial inclusion index |
|---|---|---|---|---|
| Panel A | | | | |
| Treatment effect, 4-year endline | 0.314*** | 0.256*** | 0.327*** | 0.313*** |
| | (0.034) | (0.079) | (0.029) | (0.040) |
| Treatment effect in Banerjee et al. (2015a), 3-year endline | 0.120*** | 0.113*** | 0.249*** | 0.212*** |
| | (0.024) | (0.022) | (0.024) | (0.031) |
| Panel B | (8) Physical health index | (9) Mental health index | (10) Political awareness index | (11) Women's empowerment index |
| Treatment effect, 4-year endline | 0.108*** | 0.077* | 0.269*** | 0.077 |
| | (0.027) | (0.043) | (0.091) | (0.056) |
| Treatment effect in Banerjee et al. (2015a), 3-year endline | 0.029 | 0.071*** | 0.064*** | 0.022 |
| | (0.020) | (0.020) | (0.019) | (0.025) |

Source: Bandiera et al (2017)

- Both studies find substantial effects on consumption at 7 years
- Would be nice to compare assets with cash

# CCTs

- Conditional cash transfers (e.g. Progresa) seek to break intergenerational poverty traps by conditioning cash on maternal/child health behaviors and school attendance
  - Santiago Levy: "Clearly, achieving good health is a cumulative process, and temporary investments in nutrition are of little help. The same is true of education: children must be supported year after year.... [PROGRESA's] central effects will gradually occur through the accumulation of human capital"
- These have spread rapidly over the past 20 years - more than 60 developing countries
- Short run evidence
  - Much evidence that these programs do increase health behaviors and school enrollments (e.g. Gertler 2004, Schultz 2004, Skoufias 2005)
  - Baird, McIntosh, and Ozler (2011): CCT leads to higher increase on conditioned behaviors, but some downfalls for cutting off the transfer for those who can't meet conditions
  - Benhassine et al (2015): Labeling a transfer as a CCT has about the same effects as actually enforcing the conditions

# Does this actually break the cycle of poverty?

- Key empirical challenge: most experiments treat the control group after a few years.
  - E.g. Progresa.
- But in a few cases this didn't happen. There, medium-term studies can begin to trace whether these behaviors are changing path for children
  - Cahyadi et al (2018): Indonesian CCT implemented as RCT for 6 years. Finds substantial declines in stunting for children who spend their whole life covered by the program.
  - Molina Millán et al (2018): Honduran CCT implemented for 5 years; followed 13 year after start. Substantial results on secondary and tertiary schooling (non-targeted), and increases in international migration for young men. Inconclusive for wages.
  - Baird, McIntosh, and Ozler(2016): Follow 2 year Malawi CCT 2 years later. Somewhat muted effects.
- Alternatively can use other variation
  - Parker and Vogl (2017) use cohort and geographic variation in Progresa, focusing on those exposed before age 12. Find effects on schooling, female labor force participation, and female earnings. Men and women report higher assets.
  - Aizer et al (2016) study Mothers' Pension (not a CCT but still, from 1911-1935) and find male children had more schooling and higher income in adulthood.

# Poverty traps

- On net this shows some promise:
  - Lump-sum asset transfers generate lasting static changes for recipients
  - CCTs may be creating lasting intergenerational change

# Governance

# Governance

- Third developing country challenge is governance - making sure benefits actually get delivered, and making sure targeting rules are followed
- Some (selected) examples
- Workfare in India
  - Niehaus and Sukhtankar (2013): 74 - 86 percent leakage rate in NREGS in Orissa in 2007-2008
  - Muralidharan, Niehaus and Sukhtankar (2016): 30.7 percent leakage rate in NREGS in AP in 2012
- Rice in Indonesia
  - Olken (2006): At least 18 percent of rice assistance in Indonesia didn't reach any beneficiaries
  - Banerjee et al (2018): Eligible households received only a third of intended subsidy
- Targeting in Colombia
  - Camacho and Conover (2011): Estimate 16 percent of households cheated on scores - results in bunching in PMT scores just to the left of the cutoff

# What to do about it

- This has spurred a tremendous amount of research into what to do about this problem
- Traditional approach: monitoring, audits, etc.
- But let me highlight some other approaches:
  - Payment systems
  - Information provision

# Payment Systems

- Two papers study reforms to payment systems in NREGS
- Muralidharan, Niehaus and Sukhtankar (2016) study in AP
  - Payment system reform allows direct payments to beneficiaries monitored by biometrics
  - Cuts out local government from payment flow

# Payment Systems

## Reform studied by Muralidharan, Niehaus and Sukhtankar (2016)

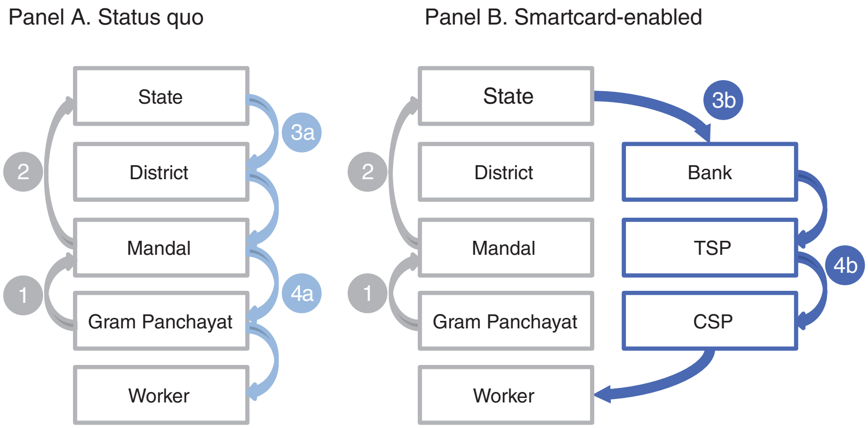



Figure 1. Comparison of Treatment and Control Payment Systems

# Payment Systems

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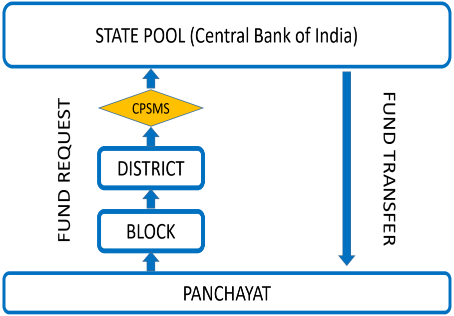
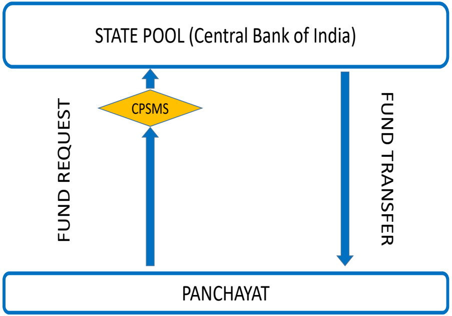
  - Payment system reform allows direct payments to beneficiaries monitored by biometrics
  - Cuts out local government from payment flow
- Banerjee et al (2019) study in Bihar
  - Replace advance payments with 'just in time' payments based on actual receipts
  - Removes several layers of bureaucracy
  - Facilitates audit

# Payment Systems

## Reform studied by Banerjee et al (2019)




(a) Control Blocks




(b) Treatment Blocks

# Payment Systems

- Both of these reforms substantially reduce leakage
- AP Smartcards Reform:
  - Reduced leakage from 30.7 percent to 18 percent (41 percent reduction)
  - Household earnings up, official outlays did not change
  - Households also received pay faster
- Bihar Payment Systems Reform:
  - Program expenditures declined 24 percent, but households report no changes in wages
  - Reduction of 5 percent in 'ghost workers' and reduction in wealth of local public officials
  - But payment delays increased
- Combined suggests there can be technocratic solutions to some of these problems - high leakage rates are not inevitable

# Information

- Can information possibly matter?
- Banerjee et al (2018) tested tangible information about beneficiary's rights under a program
  - Gave out cards with beneficiary rights
  - Creates both knowledge, and common knowledge, which can improve beneficiaries' ability to bargain

# Example card

# Public vs. private information

# Impacts of public and private information

| | Eligible Households | | | |
|---|---|---|---|---|
| | Bought in the Last 2 Months (1) | Amount Purchased (Kg) (2) | Price (Rp.) (3) | Subsidy (Rp.) (4) |
| Public information | .01 | 1.64*** | −81*** | 9,666*** |
| | (.02) | (.30) | (26) | (1,703) |
| | [.618] | [<.001] | [.001] | [<.001] |
| Standard information | .02 | .83*** | −24 | 4,839*** |
| | (.02) | (.31) | (29) | (1,764) |
| | [.349] | [.012] | [.360] | [.010] |
| Difference: public − standard | −.01 | .81** | −58** | 4,827** |
| | (.02) | (.36) | (28) | (2,031) |
| | [.717] | [.040] | [.034] | [.032] |
| Observations | 5,685 | 5,684 | 4,873 | 5,684 |
| Control group mean | .79 | 5.29 | 2,276 | 28,605 |

Source: Banerjee et al (2018)

- Suggests information can make a big difference

# Where do we go next?

# Some future challenges and directions

- Social insurance challenges for middle income countries
  - Health insurance
  - Workers compensation / workplace injuries
  - Unemployment insurance
  - Pensions

- Targeting on treatment effects
  - Heterogeneity in effects, e.g. of graduation programs
  - Can we target treatment effects?

- Broader impacts
  - What are the GE impacts of these programs?
  - Some evidence emerging on wages, migration effects of NREGS. What else?
  - Macro effects?