14.771: Breaking the Poverty trap? The "graduation" approach

Esther Duflo

Graduation

- An influential anti-poverty program is predicated on the idea that there exists a poverty trap.
- Another type of program argues that by giving people a capital infusion and help them to get started, you can help them escape poverty. In the policy space this is often referred to as “graduation.”
- Questions for today:
  1. Does this work?
  2. Is there evidence of a poverty trap
  3. Do we know where the poverty trap may be coming from?

Graduation approach in a nutshell

- Identification by community
- Asset transfert ($250 PP)
- Income support for a few weeks
- Technical support
- Group meetings/coaching/health (minor)
- Regular savings.

The additional components roughly double the cost of the transfer itself, which cost $1,000 in Bangladesh
A package intervention that is extremely expensive, with the view that you would get returns over the lifetime of the person if they stayed rich.

Does it work?

The Rubin Causal Model

(Reference: Imbens and Woolridge, 2008, Imbens and Rubin 2014).

- Consider a binary treatment W: 1 for treated, 0 for control, and an outcome Y (e.g. the treatment is : got ultra poor program, outcome is: earnings).
- Ex-ante, each individual i has two *potential outcomes*, $Y_i(1)$ if treated, $Y_i(0)$ if non-treated.

$$Y_i(obs) = Y_i(1)W_i + Y_i(0)(1 - W_i)$$

- This assume SUTVA (stable unit treatment value assumption) that treatment values for other units do not affect the outcome for a unit (otherwise we have more than two potential outcome depending on who is treated).
- The *treatment effect* for individual i is $Y_i(1) - Y_i(0)$.
- Ex-post, only one of the outcomes is realized: individual is treated or non-treated. Since no individual is observed both in the treated and non-treated state, we will not be able to estimate the treatment effect for each individual.

Estimand

- We could be interested in the average treatment effect for the population: $E[Y_i(1) - Y_i(0)]$.
- we could want to know the average treatment effect for those who receive the treatment: $E[Y_i(1) - Y_i(0)|W_i = 1]$.
- Could be interested in the average treatment for those who have some characteristics (observed or unobserved): $E[Y_i(1) - Y_i(0)|X_i = x]$, i.e. the poor, those with poor baseline achievements
- Or we may want to know other things about the treatment:
  - How the treatment is affecting the distribution in treatment and control groups (quantile treatment effects).
  - The quantile of treatment effects (this is not the same, and it is very hard to know!)

Estimating Average Treatment Effect

Suppose we have a population, with N_1 treated individual, and N_0 non treated individuals. Consider the difference between treated and control population:

$$E[Y_i(1)|W_i = 1] - E[Y_i(0)|W_i = 0]$$

$$= E[Y_i(1)|W_i = 1] - E[Y_i(0)|W_i = 1]$$

$$+E[Y_i(0)|W_i = 1] - E[Y_i(0)|W_i = 0]$$

$$= E[Y_i(1) - Y_i(0)|W_i = 1] + E[Y_i(0)|W_i = 1] - E[Y_i(0)|W_i = 0]$$

First term: ATT. Second term: difference in the underlying characteristics of the treated and non treated population (selection effect).

Assignment mechanisms

Three cases:

- The probability of assignment does not depend on potential outcomes, and is a known function of covariates (*random assignment*). this case, $E[Y_i(0)|W_i = 1] = E[Y_i(0)|W_i = 0]$ and $E[Y_i(1)|W_i = 1] - E[Y_i(0)|W_i = 0]$ is an unbiased estimate of the effect of the treatment on the treated.
- The probability of assignment does not depend on potential outcomes, but is an *unknown* function of covariates .

$$W_i \perp (Y_i(1), Y_i(0))|X_i$$

  (unconfoundness assumption, a.k.a. exogeneity, selection on observables, regular assignment). In this case, $E[Y_i(0)|W_i = 1, X = x] = E[Y_i(0)|W_i = 0, X = x]$, so the selection bias disappears if we appropriately control for x. *Matching, propensity score matching, regressions, DML estimator*, are various ways to deal with this.

Selection mechanisms (3)

- The probability of assignment depends on potential outcomes: there is a selection bias of unknown size. Program evaluation question is to find ways to deal with that. Leading strategies: *Difference-in-differences, Regression Discontinuity, Instrumental variables*.
- Special case: Latently regular assignment mechanisms.The receipt of treatment is not regularly assigned but there is a variable that assigns to treatment for which the assumption of unconfoundedness is valid. With more assumptions, one can recover causal effects (IV).

Randomized Controlled Trials

- By definition, randomized assignment solves the selection bias in the sample.
- Some remaining issues raised in the literature:
  - Uncertainty: Power (1-proba of type 2 error) depends on sample size, design, variability of the outcome of interest
  - Biases: imperfect compliance with assignment, spillovers, etc.
  - "External validity" : to what extent do the result in one site predict the results for the same program done elsewhere?
  - "Cherry picking": with multiple outcomes multiple regressions, risk to report the one result that looks good.

Graduation

- Two recent studies show remarkable effects of these transfers
  - *Bandiera et al 2017 QJE*: RCT of the BRAC ultra poor program in Bangladesh. Follows people for 4 years.
  - *Banerjee et al 2015 Science*: Similar intervention in 6 countries (Ethiopia, Ghana, Honduras, India, Pakistan, Peru), followed for 3 years.

Bandiera et al

TABLE IV

Treatment Effects on Consumption, Household, and Financial Assets of Ultra-Poor Households

	Poverty and consumption			Financial assets		
	(1)	(2)	(3)	(4)	(5)	(6)
	Below poverty line	Consumption expenditure (per adult equivalent)	Value of household assets	Household cash savings	Household receives loans	Household gives loans
Program impact after 2 years	−0.051	30.19	6.86	54.54***	0.123***	0.042***
	(0.046)	(25.34)	(7.26)	(4.60)	(0.03)	(0.01)
Program impact after 4 years	−0.084**	62.62***	39.65***	53.22***	0.110***	0.051***
	(0.038)	(20.82)	(9.08)	(4.01)	(0.03)	(0.01)
Control mean at 4-year follow-up	0.624	575.73	69.69	425	0.220	0.016
Four-year impact: % change	−13.5%	11%	57%	24%	50%	319%
2-year impact = 4-year impact [p-value]	0.379	0.111	0.000	0.781	0.714	0.527
Adjusted R-squared	0.032	0.044	0.082	0.204	0.086	0.026
Number of ultra-poor women	6,732	6,732	6,732	6,732	6,732	6,732
Observations	18,882	18,838	20,196	20,179	20,196	20,196
(clusters)	(40)	(40)	(40)	(40)	(40)	(40)

Banerjee et al

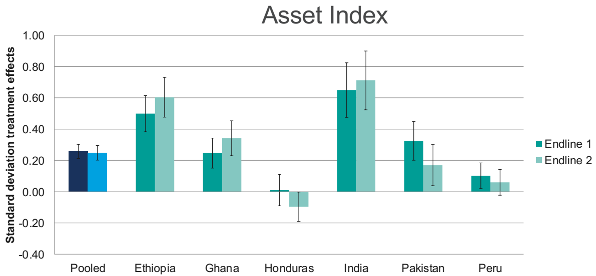
Table 3. Indexed family outcome variables and aggregates.

	Endline 1			Endline 2		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Indexed outcomes	**Standardized mean treatment effect**	***q*-value for all 10 hypotheses**	***F*-test of equality of coefficients across sites, with *q*-values**	**Standardized mean treatment effect**	***q*-value for all 10 hypotheses**	***F*-test of equality of coefficients across sites, with *q*-values**
Total per capita consumption, standardized	0.122*** (0.023)	0.001	3.207 0.009	0.120*** (0.024)	0.001	5.307 0.001
Food security index (five components)	0.107*** (0.022)	0.001	1.670 0.139	0.113*** (0.022)	0.001	2.405 0.050
Asset index	0.258*** (0.023)	0.001	14.26 0.001	0.249*** (0.024)	0.001	23.90 0.001
Financial inclusion index (four components)	0.367*** (0.030)	0.001	55.33 0.001	0.212*** (0.031)	0.001	10.70 0.001
Total time spent working, standardized	0.090*** (0.018)	0.001	7.520 0.001	0.054*** (0.018)	0.004	2.644 0.038
Incomes and revenues index (five components)	0.383*** (0.036)	0.001	12.05 0.001	0.273*** (0.029)	0.001	5.82 0.001
Physical health index (three components)	0.034* (0.019)	0.078	3.825 0.003	0.029 (0.020)	0.159	0.776 0.630
Mental health index (three components)	0.099*** (0.022)	0.001	5.189 0.001	0.071*** (0.020)	0.001	1.781 0.142
Political Involvement index (four components)	0.064*** (0.018)	0.001	4.176 0.002	0.064*** (0.019)	0.002	2.624 0.038
Women's empowerment index (five components)	0.046** (0.023)	0.049	1.803 0.121	0.022 (0.025)	0.385	0.469 0.800

Features to note in the Banerjee et al. study

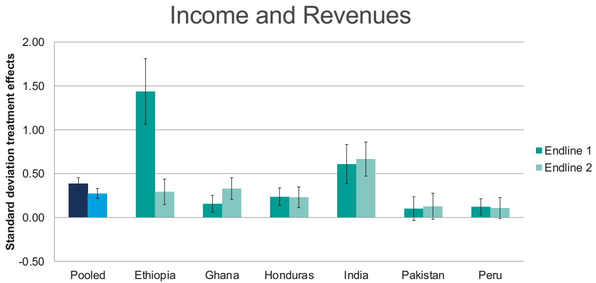
- Several sites
- Same program, BRAC inspired, coordinated (regular meetings).
- Group outcomes into indexes
- Corrects standard errors for multiple outcomes.

Country by Country results



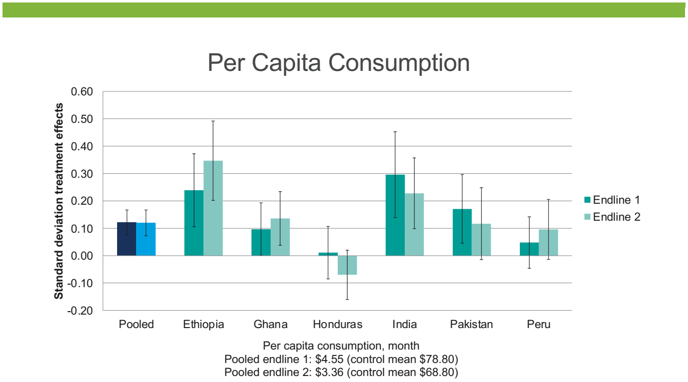
Total asset value
Pooled endline 1: $599 (control mean $2619)
Pooled endline 2: $533 (control mean $2300)

Country by Country results



Monthly livestock revenues
Pooled endline 1: $85.81 (control mean $73.52)
Pooled endline 2: $55.50 (control mean $80.62)

Country by Country results

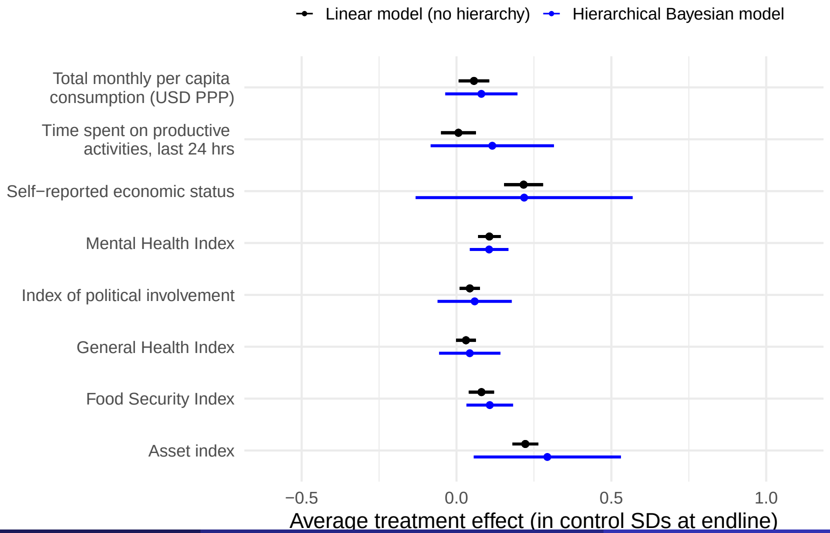


Are the results similar or different? Bayesian hierarchical analysis

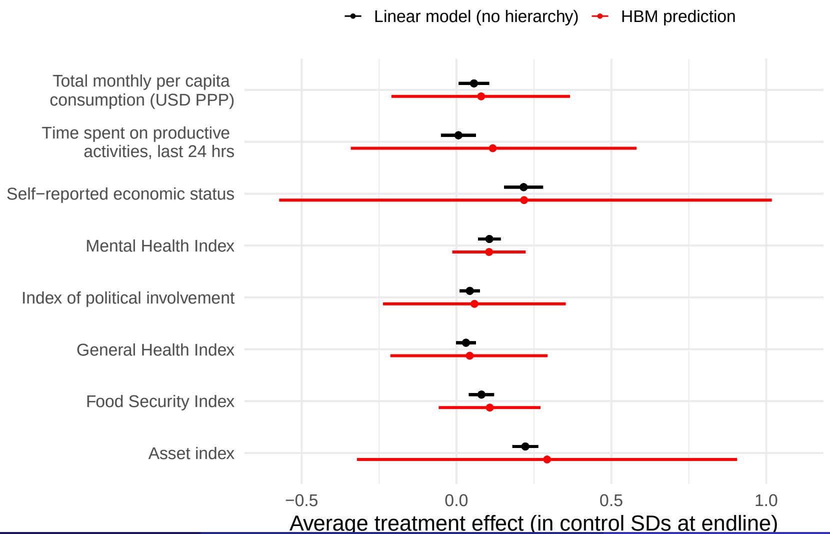
Meager, et a.

- Basic idea: results are different in different countries for two reasons:
  - There is noise in the estimate
  - The estimates are different
- BHM assumes that treatment effect are drawn from a normal distribution, with some variance
- It uses the data sets to estimate the mean and the variance of the treatment effects.
- Country-level estimates will tend to get closer together as their "borrow" some of their precision from other studies
- And we get an ideal of the heterogeneity of the treatment effect from site to site.

BHM vs Frequentist Pooled Reg (Endline 1)



Predictive effects suggest major heterogeneity across studies



Cost-benefit

- Two key issues.
- *Costs*.
    - These programs are really, really expensive.
    - Only 'worth it' if benefits persist long into the future.
    - Recall Bandiera et al 2017 Table IV. After 4 years, consumption is about 11 percent higher.
    - In cost-benefit, they assume those consumption increases last until year 20.
    - The depreciation rate of benefits turns out to be key.

Cost-benefit

TABLE IX

Cost-Benefit Analysis

Panel A: External parameters	
Cost per household at year 0	1,121.34
Cost per household discounted at year 4	1,363.00
Social discount rate = 5%	
Panel B: Estimated consumption benefits	
1 Change in household consumption expenditure year 1	61
2 Change in household consumption expenditure year 2	106
3 Change in household consumption expenditure year 3	237
4 Change in household consumption expenditure year 4	345
5 NPV Change in household consumption expenditure from year 5 for 20 years	3,581
6 Change in household assets year 4	40
7 Total benefits (1+2+3+4+5+6)	4,369
8 Benefits/cost ratio (assuming benefits last 20 years from transfer date)	3.21
Sensitivity to different discount rates/time horizons	
Social discount rate = 10%	2.50
Benefits last 10 years from transfer date	1.86
Benefits last 5 years from transfer date	0.82
9 IRR (assuming benefits last 20 years from transfer date)	0.22
Sensitivity to different outside options/time horizons	
Wage jobs available all year at $0.34 per hour	0.16
Benefits last 10 years from transfer date	0.17
Benefits last 5 years from transfer date	−0.01
Panel C: Estimated asset benefits	
10 Change in productive assets year 4	1,030.50
11 Change in financial assets year 4	85.10
12 Increase in assets/asset cost	1.85

Cost-benefit

Table 4. Cost-benefit analysis.

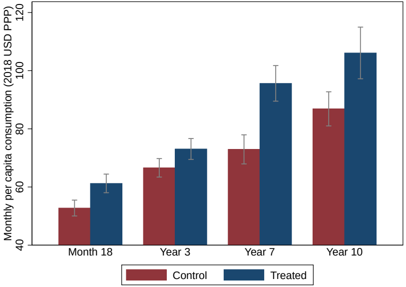
Panel A: Program costs per household, USD PPP 2014	Ethiopia	Ghana	Honduras	India	Pakistan	Peru
Direct transfer costs	1228	680	724	700	2048	1095
(1) Asset cost	1228	451	537	437	1043	854
Food stipend	0	229	187	263	911	241
Total supervision costs	1900	2832	1633	407	–	3357
Salaries of implementing organization staff	347	1994	801	297	–	2477
Materials	33	119	112	1	–	55
Training	850	44	121	19	–	111
Travel costs	174	293	210	17	–	55
Other supervision expenses	496	382	388	73	–	660
Total direct costs	3127	3513	2356	1107	4680	4452
Start-up expenses	43	133	104	38	–	45
Indirect costs	421	1026	209	112	470	462
Total costs, calculated as if all incurred immediately at beginning of year 0	3591	4672	2670	1257	5150	4960
(2) Total costs, inflated to year 3 at 5% annual discount rate	4157	5408	3090	1455	5962	5742
Exchange rate to PPP adjustment scalar	3.41	2.19	1.90	3.52	4.44	1.84
Panel B: Benefits per household, USD PPP, all values inflated or deflated to year 3 at 5% annual social discount rate						
(3) Year 1 annual nondurable consumption ITT, assuming treatment effect equal to year 2	451	293	66	344	613	339
(4) Year 2 annual nondurable consumption ITT treatment effect	451	293	66	344	613	339
(5) Year 3 household asset ITT treatment effect	63	15	−20	6	7	37
(6) Year 3 nondurable annual consumption ITT treatment effect	424	332	−218	251	451	263
(7) Year 4 onward total consumption ITT treatment effect, assuming year 3 gains persist in perpetuity	9417	6241	−6011	5354	8994	7402
(8) Total benefits: (3) + (4) + (5) + (6) + (7) = (8)	10805	7175	−6118	6298	10678	8380
(9) Year 3 productive asset ITT treatment effect	851	118	32	171	163	59
(10) Year 3 savings balance ITT treatment effect	272	11	32	9	7	45
Panel C: Benefit/cost ratios						
(11) Total benefits/total costs ratio: (8)/(2) = (11)	260%	133%	−198%	433%	179%	146%
Increase in asset value in year 3						
(12) (Household, productive and financial)/cost of asset transfers: [(5) + (9) + (10)]/(1) = (12)	97%	32%	8%	43%	17%	16%
(13) Increase in asset value/transfers, 10th percentile	56%	5%	−3%	1%	2%	7%
(14) Increase in asset value/transfers, 25th percentile	72%	12%	8%	10%	7%	8%
(15) Increase in asset value/transfers, 50th percentile	85%	20%	15%	23%	15%	7%
(16) Increase in asset value/transfers, 75th percentile	123%	29%	20%	58%	45%	16%
(17) Increase in asset value/transfers, 90th percentile	175%	37%	32%	131%	52%	7%
Sensitivity analysis						
(18) Internal rate of return (IRR)	13.3%	6.9%	–	23.4%	9.5%	7.5%
(19) Annual rate of dissipation of the treatment effect such that costs = benefits	10.3%	1.8%	–	31.1%	5.0%	2.6%
(20) Benefit/cost ratio, at discount rate of 7%	182%	93%	−132%	306%	127%	102%
(21) Benefit/cost ratio, at discount rate of 10%	124%	63%	−84%	211%	88%	69%

- Line 19 calculates dissipation rate of treatment effect for break-even

Are results persistent?

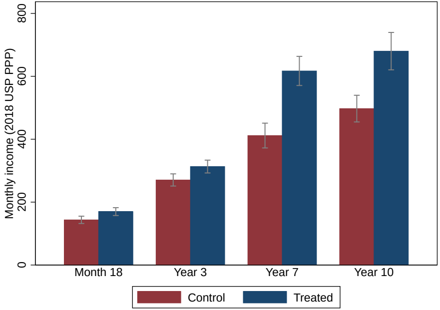
Banerjee, Duflo, Sharma, 2021: Evidence from India

Per capita consumption (2018 USD PPP) persistently higher for TUP hh



- Treatment effect grows and persists: 0.3 SD; 0.3 SD; 0.7 SD; 0.6 SD.
- Control level at four endlines: \$1.8/day, \$2.2/day, \$2.4/day, \$2.9/day.
- Extreme poverty definition: \$2.1/day; Moderate poverty definition: \$3.5/day.

Income (2018 USD PPP) persistently higher for TUP hh



- Treatment effect grows and persists: 0.15 SD; 0.15 SD; 0.33 SD; 0.26 SD.

Are results persistent?

Positive effect on food security, physical, mental health

	Food security	Financial inclusion	Physical health	Mental health
		18 months		
Treatment	0.184***	-0.004	0.061**	0.115***
	(0.048)	(0.042)	(0.028)	(0.029)
Control Mean	0.35	0.14	0.12	0.32
		3 years		
Treatment	0.251***	0.192***	0.027	0.012
	(0.059)	(0.062)	(0.027)	(0.037)
Control Mean	0.94	0.30	0.21	0.75
		7 years		
Treatment	0.431***	0.181	0.130***	0.249***
	(0.062)	(0.135)	(0.031)	(0.042)
Control Mean	1.09	0.67	0.57	1.09
		10 years		
Treatment	0.127**	0.121	0.187***	0.203***
	(0.063)	(0.152)	(0.040)	(0.044)
Control Mean	1.21	1.08	0.12	0.76

- Similar pattern of growth, persistence.
- In baseline standard deviation units: index creates z-scores, standardizes to baseline.

Details

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Are results persistent?

Positive effect on assets, but declines by year 10

	Asset index	Productive	Household
		18 months	
Treatment	0.222**	0.467***	0.125
	(0.111)	(0.087)	(0.092)
Control Mean	-0.19	-0.23	-0.12
		3 years	
Treatment	0.389***	0.571***	0.245**
	(0.103)	(0.072)	(0.098)
Control Mean	-0.25	-0.30	-0.17
		7 years	
Treatment	0.814***	0.795***	0.600***
	(0.132)	(0.083)	(0.118)
Control Mean	-0.46	-0.40	-0.35
		10 years	
Treatment	0.346***	0.197*	0.245**
	(0.121)	(0.105)	(0.113)
Control Mean	-0.26	-0.10	-0.21

- Principal component analysis + z-scores.
- Households diversify income source by year 10: up next.

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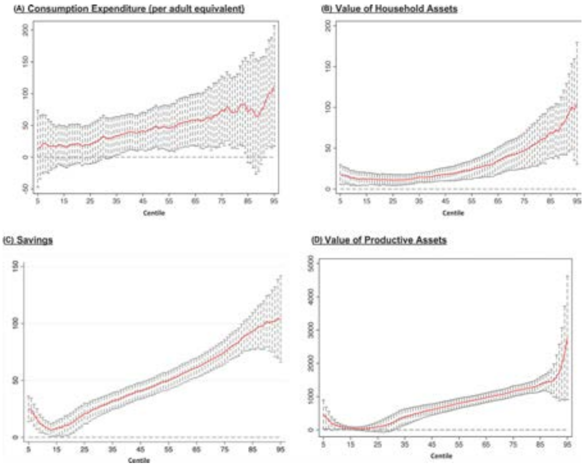
Updated cost benefit analysis

- Costs in India (2018 USD PP) $2048 (of which direct transfer is 56%)
- Breaks even by year 4
- Return: 351% by year 10; 510% if 10-year consumption gains persist until year 15; 1123% if in perpetuity.

Cost-benefit

- Two key issues.
- *Costs*.
  - These programs are really, really expensive.
  - Only 'worth it' if benefits persist long into the future.
  - Recall Bandiera et al 2017 Table IV. After 4 years, consumption is about 11 percent higher.
  - In cost-benefit, they assume those consumption increases last until year 20.
  - The depreciation rate of benefits turns out to be key.
- *Heterogeneity*.
  - These programs have highly heterogeneous returns.
  - Examine using quantile treatment effects.

Heterogeneity



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    - The depreciation rate of benefits turns out to be key.
- *Heterogeneity*.
    - These programs have highly heterogeneous returns.
    - Examine using quantile treatment effects.
    - A key question is therefore: how do you identify the people with highest returns?

Poverty trap?

- Persistent impact of temporary transfer in India suggests that there is a poverty trap
- Similar results in Bangladesh (though randomization is lost after year 4).
- Direct evidence of the S-shape mechanism?
- Balboni, Bandiera, Burgess, Ghatak and Heil, 2021 “Why do people stay poor”

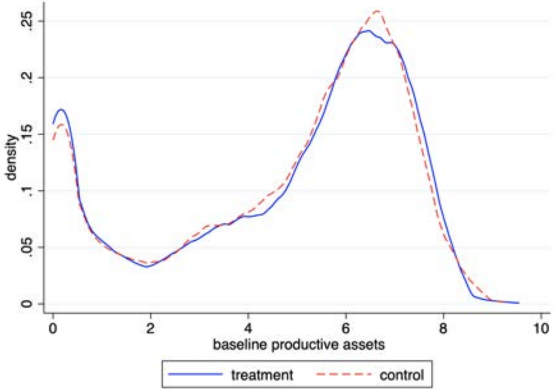
Why do people stay poor?

- One of the first serious attempt to draw a "S-curve" at the individual level (there has been other effort to establish non convexity in returns to investment of small firms that we will see later).
- Some people had been skeptical... (Kray and McKenzie)
- However what is the main empirical problem with observational data ?
- It is that you would not expect to see anyone precisely near the unstable steady state: they would be pushed either side towards the stable steady state.
- So what would we be expected to see for the distribution of assets?
- Bimodal distribution

Bimodal distribution of asset in Bangladesh ultra poor villages

Figure 1: Distribution of Productive Assets in Bangladeshi Villages: all Wealth Classes

(a) Distribution of Productive Assets at Baseline



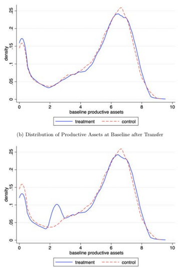
How does the ultra poor program help us?

- What would have been the ideal experiment to identify a poverty trap?
- That was not the experiment conducted, but how does it come relatively close?
- Depending on original wealth, for some treatment people the transfer was enough to move them above the threshold, and for some, not.

Bimodal distribution of asset in Bangladesh ultra poor villages

Figure 1: Distribution of Productive Assets in Bangladeshi Villages: all Wealth Classes

(a) Distribution of Productive Assets at Baseline

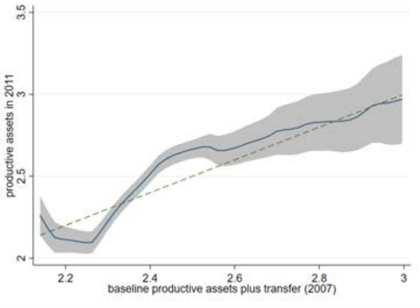


Notes: The graph shows kernel density estimates of the distribution of baseline productive assets in the full sample of 21,839 households across all wealth classes in treatment and control villages. Productive assets are measured as the natural logarithm of the total value, in 1,000 Bangladeshi Taka, of all livestock, poultry, business assets, and land owned by the households. Sample weights are used to account for different sampling probabilities across wealth classes. The weights are based on a census of all households in the 1,309 study villages. Panel b) shows the post-transfer distribution. Transfers for treatment households are imputed as the median value of a cow within the catchment area of a household's BRAC branch.

Same distribution as previous figure but impute the median value of a cow.

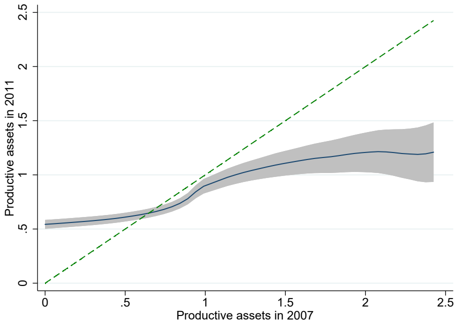
Transitional equation, treatment villages

Figure 4: Local Polynomial Estimates of the Transition Equation



(a) Treatment villages

Transitional equation, control villages



(b) Control villages

S shape but just one steady state

Estimation using the control group as counterfactual

- Define $\Delta_i = k_3 - k_1$
- Define $\widehat{k}$ as the threshold level of capital, where the S-curve in figure 4(a) crosses the 45 degree lines (which we can just estimate once we have the non parametric estimation equation).
- Figure suggest that if baseline capital+transfer is below $\widehat{k}$, Δ_i should be negative, and above $\widehat{k}$, it should be positive
- To get a counterfactual of how someone with that level of capital *would* have grown, we use the control group and assign to them their baseline+ the transfer they would have gotten.
- We then run an interaction specification.

Difference in difference estimate, above and below the threshold (with transfer)

	Dependent variable: Δ_i					
	(1) Treatment	(2) Control	(3) Both	(4) Treatment	(5) Control	(6) Both
above $\hat{k}$	0.297***	-0.020	-0.020	0.475***	-0.097	-0.097
	(0.043)	(0.052)	(0.057)	(0.070)	(0.598)	(0.669)
Treatment			-0.483***			0.398
			(0.059)			(0.664)
above $\hat{k}$ × Treatment			0.318***			0.571
			(0.070)			(0.672)
Baseline assets				-2.199***	-0.463*	-0.463
				(0.698)	(0.266)	(0.298)
above $\hat{k}$ × Baseline assets				1.969***	-0.097	-0.097
				(0.729)	(0.269)	(0.301)
Treatment × Baseline assets						-1.737**
						(0.716)
above $\hat{k}$ × Treatment × Baseline assets						2.067***
						(0.744)
constant	-0.138***	0.345***	0.345***	-0.282***	-0.680	-0.680
	(0.033)	(0.046)	(0.050)	(0.057)	(0.592)	(0.662)
N	3292	2450	5742	3292	2450	5742

Notes: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$. Standard errors in brackets. Sample: ultra-poor households in treatment and control villages with log baseline productive assets below 3 (Observations from control households are excluded if their baseline productive assets were above 3 if they had received the transfer). The dependent variable is the difference between log productive assets in 2011 and log of productive assets in 2007, where productive assets are defined as the total value of livestock, poultry, business assets (e.g. tools, vehicles and structures), and land. Above $\hat{k}$ equals 1 if the baseline asset stock plus the imputed transfer is larger than 2.333, and 0 otherwise. In treatment, this represents households' actual post-transfer asset stock. In control, where no transfer was received, above $\hat{k}$ indicates if the household would be above 2.333 if it had received a transfer. Baseline assets always refers to the actual level of assets, i.e. without the imputed transfer in control. Treatment was assigned at the village level. Baseline assets are centered at 2.333, i.e. the value reflects the log of household's productive assets in 2007 minus 2.333.

Where does the poverty trap really come from?

- Balboni et al, take the transition equation very literally to be something about assets.
- Banerjee et al. insist on the diversification of household businesses across the endline, and for the last endline the role of distant migration (or the younger generation).
- Karlan et al (Ghana), have an explanation that is related to "capability". They show that people who get the TUP transfer work more productively on work requiring focus (behavioral explanation–we will get back to this after we study a bit more behavioral).

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