Using Randomised Control Trials to Evaluate Policies

Bansi Malde

EDePo, Institute for Fiscal Studies

December 2013

Outline

- Why Evaluate Policies?

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- The Evaluation Problem

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- Randomised Control Trials (RCTs)
    - How do these work?
    - Limitations of RCTs

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- Application:
  - RCTs in Development: Providing Information on Child Nutrition in Rural Malawi

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- Field experiments offer useful exogenous variation to
    - Estimate parameters
    - Test models and theories

The Evaluation Problems

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- Specific Obstacles: selection and endogeneity

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  - Long term trends
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  - Long term trends
  - Macroeconomic changes
- Naively comparing outcomes for those who received the policy with those that did not receive the policy may also not be valid evaluation
  - Selection Effects

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- We want to establish whether and how a policy, T affects the outcome of interest Y_i; $i = \{1, ..., N\}$
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    - Y_i could be health, income, employment, tax payments, etc
- Looking for counterfactuals: What would have happened to this person's behaviour in the absence of the policy or under an alternative policy?
    - Example: Do people earn more when they have more education?

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- **Missing data problem**

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- Average outcome of the treated: $E(Y_i^1 | T_i = 1)$
- Average outcome of the control: $E(Y_i^0 | T_i = 0)$
- Difference between averages:
  $D = E(Y_i^1 | T = 1) - E(Y_i^0 | T_i = 0)$

Selection Bias

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- Examples of selection bias: Evaluating a policy to get the long-term unemployed back to work by comparing the employment outcomes of those who took up policy with those who didn't
  - Those who took up policy may have been more motivated and hence more likely to get a job anyways

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- $D = E(Y_i^1|T=1) - E(Y_i^0|T=0) = \alpha = E(Y_i^1 - Y_i^0)$
- Can easily obtain convincing results, BUT only if trial has been well designed and implemented
    - Non-trivial issues

Designing RCTs

Partners

- RCTs involve working with partners, e.g. government, NGOs, who implement the policy/intervention
- Important to work with partners that understand the methodology of RCTs

Define study population

- What is the target population?

Define outcome of interest

- What is the main outcome targeted by the policy?
- Multiple outcomes

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- Large sample may be costly, but small sample may only be able to detect very large effects

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- Choice depends on:
  - The intervention: who does it target?
  - Spillovers: Will the policy affect those not treated?
  - Implementation constraints:
    - Fixed costs of implementation $\rightarrow$ cost-efficient to randomise at the group level
    - Withholding policy from sub-set of group may cause resentment toward implementation organisation
    - Greater scope of mistakes from field staff

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- Hawthorne and John Henry effects: Units react differently because they know that they are part of an experiment

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- They cannot be used to evaluate policies that cannot be excluded from some individuals or groups, for example, monetary policy

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    - Understanding why a policy worked can help in this
  - Would it be as effective if implemented by another provider?
  - Would impacts be the same if implemented at a different scale?
    - Pilot project vs. Nationwide rollout

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- Uncover channels through which outcomes change
    - These can be tested
    - Detailed example to follow
- Researchers have been designing RCTs in order to test economic theory
    - Example: Ashraf, Karlan and Yin (2006) test the importance of time-inconsistent preferences in explaining saving behaviour

Application: Providing Information on Child Nutrition in Rural Malawi

- Evaluate a cluster randomized control trial in rural Malawi which provided mothers with information on child nutrition via home visits
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- Interested in:
  - Impacts on child health, the key outcome the intervention intended to improve
  - Understanding how the impacts were realised

Setting: Mchinji (Malawi)

- Child health is very poor in Malawi
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  - 48% of kids aged < 5 years are too short for their weight (i.e. stunted)
- Factors influencing child health include prenatal maternal behaviour, nutrition, disease environment
- One constraint driving such poor health outcomes is that households don't know how best to feed their infants
  - Common to give porridge with unsterilized water to infants as young as 1 week
  - 1/3 of kids aged 6-54 months do not consume any proteins over a 3 day period

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- Intervention began in July 2005 and is still on-going

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- Considerations taken into account when designing the experiment include:
  - Spillovers, esp. cross-village spillovers
  - Implementation costs

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- Remaining 24 received another intervention focused on maternal health

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- Households have limited resources $\rightarrow$ budget constraint

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  - Depends on degree of substitutability of A and L
- Increase in C is more than decrease in A $\rightarrow$ total household consumption will increase

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    - Sample of 1660 women and their households
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- The sample is balanced on a broad set of woman and household socio-economic characteristics, suggesting randomisation worked

Empirical Model

- With an RCT, we can simply compare means

$$Y_{ict} = \alpha + \beta_1 T_c + \mathbf{X}'_{ict}\beta_2 + \mathbf{Z}'_{c0}\beta_3 + \mu_t + u_{ict}$$

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- Inference:
    - Wild cluster bootstrap-t (Cameron, Gelbach and Miller 2008)
    - Randomization Inference (Fisher 1935; Rosenbaum 2002)

Empirical Framework

- Study impact of the following outcomes along the causal chain and suggested by theory to uncover how intervention worked:
    - Maternal nutritional knowledge
    - Child consumption
    - Household consumption
    - Labour supply
    - Child health

Nutritional Knowledge

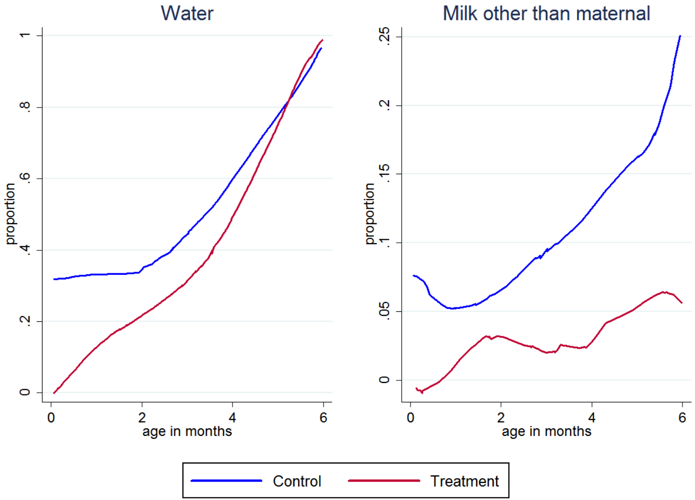
- Index computed from responses to 7 questions on child nutrition

	Summary Index	Breastfeeding when infant has diarrhoea	Best way of cooking fish with porridge for infant aged > 6 months?
T_c	0.169+	0.253+	0.067**
Standard Error	[0.086]	[0.115]	[0.019]
Wild Cluster Bootstrap p-value	{0.058}	{0.084}	{0.002}
Randomization Inference p-value	{0.065}	{0.028}	{0.008}
Observations	1512	1512	1512
IntraCluster Correlation	0.169	0.277	0.057
Mean, Control	-0.04	0.217	0.026

Notes: ** Significant at 1% level, * at 5% level, + at 10% level

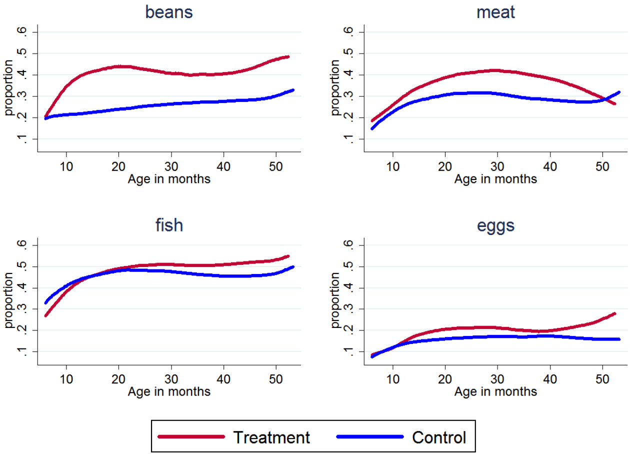
Child Consumption

- Significant improvements in consumption among children aged < 6 months:



Child Consumption II

- Significant improvements in diets of children >6 months and born after July 2005



Household Consumption

	[1]	[2]	[3]	[4]	[5]
		Per Capita Monthly Food Consumption for:			
	Summary Index	**Cereals**	**Proteins**	**Fruit and Vegetables**	**Other Foods**
T_z	0.218*	-9.878	128.359*	269.819+	60.453
Standard Error	[0.082]	[52.450]	[54.798]	[108.600]	[33.561]
Wild Cluster Bootstrap p-value	{0.018}	{0.931}	{0.022}	{0.060}	{0.150}
Randomization Inference p-value	{0.037}	{0.952}	{0.016}	{0.042}	{0.020}
Observations	3200	3205	3202	3204	3204
R-squared	0.063	0.118	0.02	0.195	0.024
IntraCluster Correlation	0.087	0.074	0.042	0.172	0.053
Mean Control Areas	-0.10	606.00	349.80	679.70	149.70

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How is the increased consumption funded?

	Male Adults			
	[1]	[2]	[3]	[4]
	Summary Index	Works	Has at least 2 jobs	Weekly Hours Worked
T_z	0.262+	0.096	0.072*	4.31
Standard Error	[0.131]	[0.078]	[0.028]	[2.918]
Wild Cluster Bootstrap p-value	{0.074}	{0.303}	{0.020}	{0.230}
Randomization Inference p-value	{0.062}	{0.251}	{0.057}	{0.202}
Observations	3642	3961	3958	3642
R-squared	0.183	0.17	0.05	0.16
IntraCluster Correlation	0.146	0.208	0.036	0.100
Mean, Control	-0.135	0.836	0.122	25.740

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- No impacts on female labor supply

Child Health

	[1]	[2]	[3]	[4]
	Summary Index	**Height for Age**	**Healthy weight for age**	**Healthy weight for height**
T_z	0.102*	0.271*	0.030	0.048
Standard Error	[0.036]	[0.102]	[0.019]	[0.027]
Wild Cluster Bootstrap p-value	{0.022}	{0.022}	{0.150}	{0.132}
Randomization Inference p-value	{0.035}	{0.055}	{0.312}	{0.147}
Observations	2175	2192	2265	2217
R-squared	0.026	0.046	0.024	0.029
IntraCluster Correlation	0.021	0.022	0.018	0.017
Average, Control	0.266	-2.338	0.817	0.845

Notes: ** Significant at 1% level, * at 5% level, + at 10% level

- Positive but statistically insignificant impacts on physical growth for children aged < 6 months

Concluding Remarks

- RCTs can provide a credible counterfactual group for policy evaluation
- Gold standard evaluation method
- Careful design needed, taking into account implementation constraints
- Limitations to what they can tell us
- Economic modelling has a role to play

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