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AT URBANA-CHAMPAIGN

The Challenge of Impact Assessment

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Outline for the Session

1. Why do we do impact assessment?
2. How do we do impact assessments?
3. Solutions to the Fundamental Problem of Causal Inference
4. Approaches to measuring the treatment effect
5. Implementing an impact assessment

Why Do We Do Impact Assessment?

Why Do We Do It?

- Want to estimate the impact of a policy or program

$$T \longrightarrow M \longrightarrow Y_t$$

Treatment (Program Intervention) | Mechanism | Outcome

Theory of Change

- Define treatment and anticipated outcomes, mechanisms and moderators
  - What are we doing, what are we hoping it does and how do we think it will work?
- Not trivial; multiple outcomes at multiple scales (water plus biodiversity, economic development)
- Defining measures of outcomes can also be complicated
- Get potential confounders and insight into program design

Context

- Need to understand the context and program rules
  - Who was eligible?
  - Who signed up or dropped out (selection bias); e.g. livestock adoption
  - Particularly important in non-experimental settings
  - Key to understanding potential confounding factors (e.g. certain sanitation initiatives may be culturally unacceptable)

How Do We Do Impact Assessment?

Fundamental Problem of Causal Inference

- Do not observe subject in simultaneous treated and untreated states
- We only observe one state for each unit, Y_i^T or Y_i^C

$$\delta = Y_i^T - Y_i^C$$
$$E[\delta] = E[Y_i^T - Y_i^C]$$

Compared to What?

- We want to compare the outcomes of the program to what would happened otherwise

$$T \rightarrow M \rightarrow Y_t$$
$$C \longrightarrow Y_c$$

Counterfactual

- Evaluated in the context of a Counterfactual: what would have happened otherwise?
- Can create a counterfactual (medical trials) or can estimate one.
- To consider why the program had an effect, one needs to have similar characteristics (and similar heterogeneity) in treatment and control groups.

Assumptions

- SUTVA (Stable Unit Treatment Value Assumption)
- Unconfoundedness/Ignorability

Solutions to the Fundamental Problem of Causal Inference

The Problem

- We want to estimate the effect of a policy that targets a specific area

Policy (Treatment)

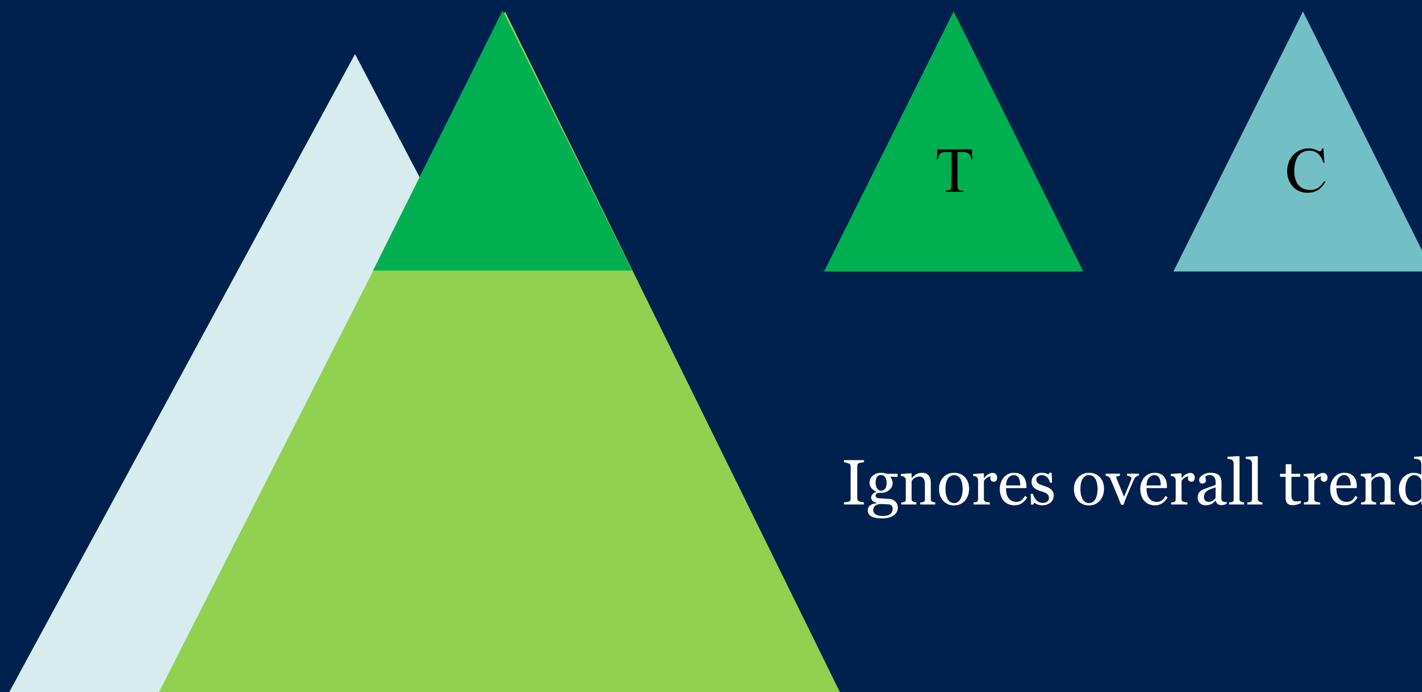
Issue: *what would have happened without the policy?*

Choice of location for policy is not random.

It is (somehow) different than other locations not chosen.

The rocks and ice problem

Traditional Approach: Before vs After



Ignores overall trend

Traditional Approach: Inside vs Outside

Ignores how location affects outcome.

An Example: Water Use (Ferraro, 2009)

- Water conservation program to reduce residential water use
- Found average water consumption declined 29%
- Expanded to new neighbourhood where consumption declined 38%
- Great Program!

But….

Rain increased and untreated neighbourhood saw its consumption decline 31%

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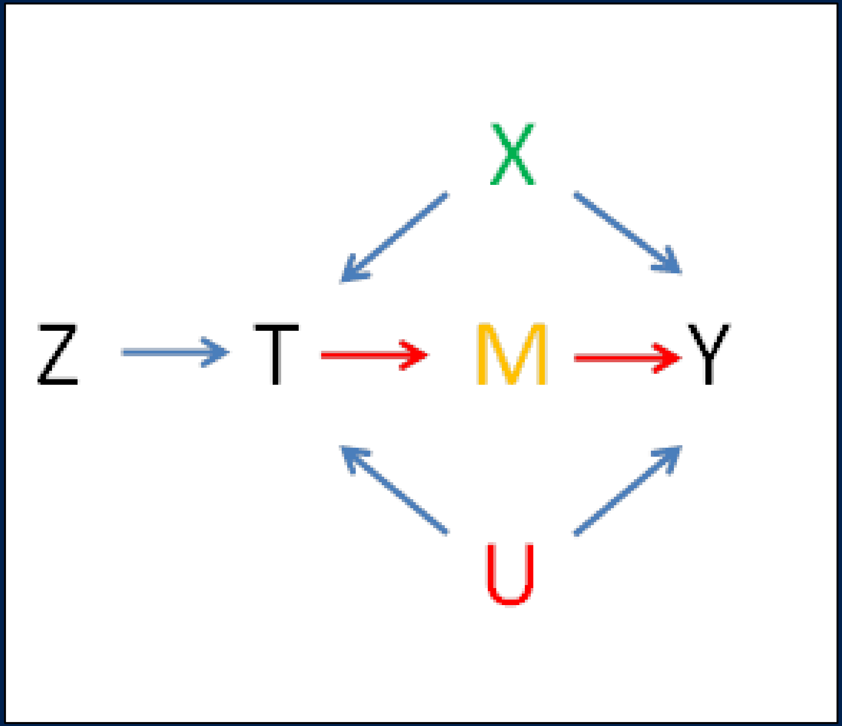
Not There Yet…

- Much so-called evaluation of program impact is simply monitoring of indicators (did the number of hybrid cars on the road go up? Not necessarily: Did air pollution go down?) and certainly not counterfactual thinking
- Realistic theories of behaviour generate ambiguous predictions about impacts.
- Many confounding factors correlated with timing and location of interventions (weather in the previous example; milk weed in US; prices in logging)
- Selection bias
- Thus need counterfactual thinking to sort out true impact.

Schematic



- Interested in the effect of Treatment T on outcome Y
- Treatment affects outcome through mechanism M
- Observables, X, can affect both probability of treatment and outcome.
- Unobservables, U, can affect both probability of treatment and outcome
- Other factors, Z, affect selection into Treatment but not outcome directly

An Example: Agroforestry

- Free seedlings (T) create an incentive for households to incorporate trees into agriculture *(M),* decreasing soil erosion (Y)

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An Example: Agroforestry

- Free seedlings (*T*) create an incentive for households to incorporate trees into agriculture *(M),* decreasing soil erosion (*Y*)
- Only some randomly-chosen districts get the program (*Z*)
- Adopters have more household labour than those who do not (*X*)
- Households who are more concerned about environmental outcomes are more likely to adopt (*U*)

An Example: Livestock

- Livestock (T) increase income ($M1$) and reduce cost of animal foods ($M2$), which increase household food security (Y)
- Households need certain level of assets (X) to care for animals
- More nutritionally-minded households may both be more likely to successfully adopt livestock and to better feed their children (U)

Approaches to Measuring the Treatment Effect

Approaches to Estimation

1. Create variation in *T* that is unrelated to the outcomes. Eliminate *X* and *U* as rival explanations. Focus on treatment effect through mechanisms
   - *RCT*
   - *Randomized Roll-out*
   - *Randomize access or information*

Approaches to Estimation

2. Condition effect of treatment on *X*
    - *Matching*
    - *Difference-in-differences*

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2. Condition effect of treatment on X
   - *Matching*
   - *Difference-in-differences*

   (problem is the U)

Matching

- Find a set of ‘matched’ control (untreated) parcels with similar characteristics to the treated parcels
- If we do a good job finding control parcels that look like the treated parcels, we can replicate what would have happened without protection*

*Assumes unobservable characteristics are distributed in the same way as observables: i.e. Matching over observables = matching over unobservables

Difference-in-Difference (DiD)

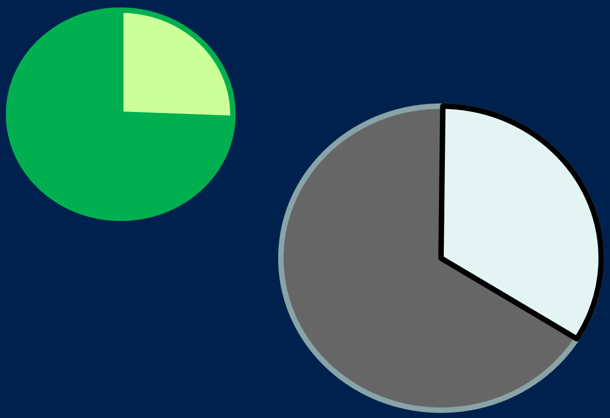
	Treatment (Reserve + Payment)	Control (outside Reserve)
Before	To	Co

Caveats:

- Control and Treatment groups should be similar
- Choice of Treated cannot be correlated with unobservables that affect outcome
- Control must be 'uncontaminated'. i.e. not affected by treatment
- Works best with random placement. Very rare.

Difference-in-Difference (DiD)

	Treatment (Reserve + Payment)	Control (outside Reserve)
Before	T0	C0
After	T1	C1



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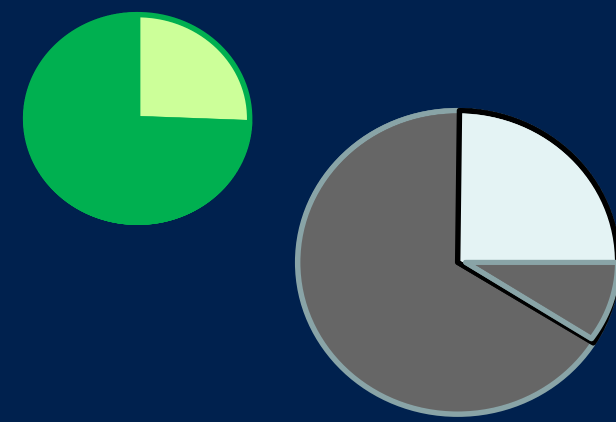
Difference-in-Difference (DiD)

	Treatment (Reserve + Payment)	**Control (outside Reserve)**
Before	T0	C0
After	T1	C1
Change	ΔT	ΔC



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Before	T0	C0
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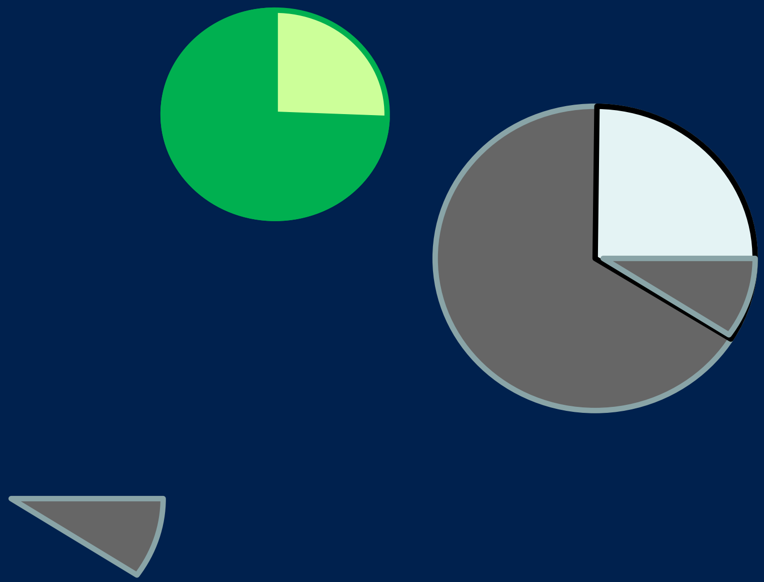
Change	ΔT	ΔC
Difference in Difference	**ΔT - ΔC**	



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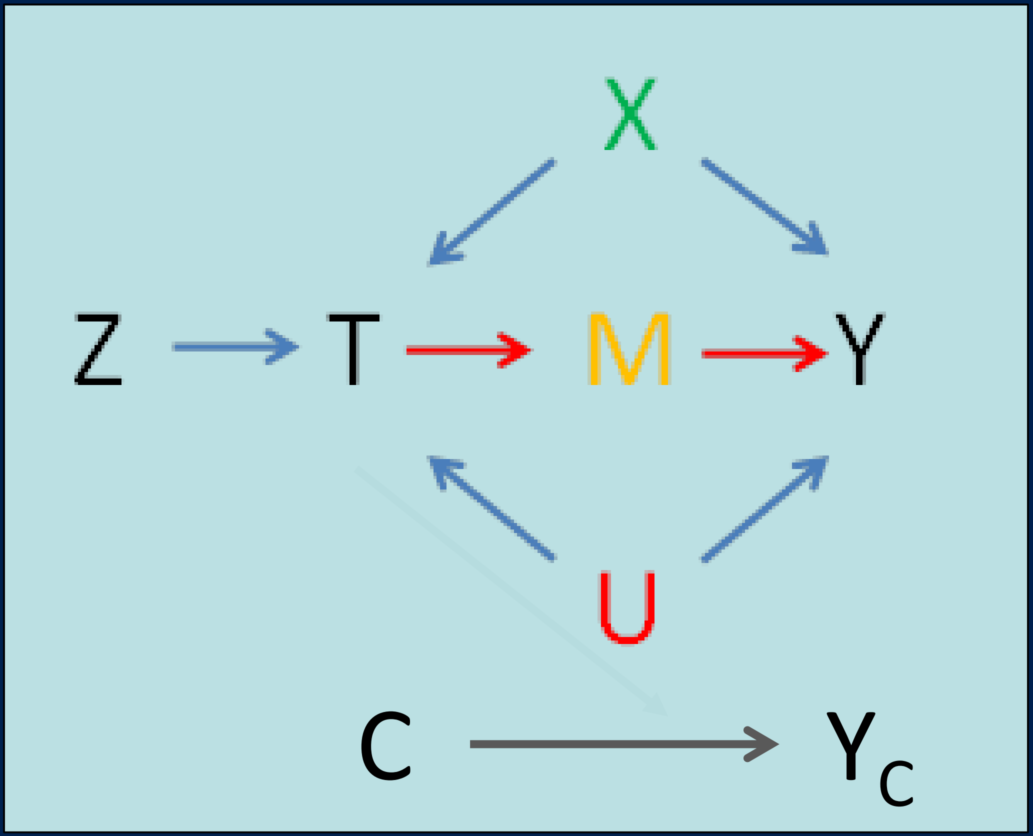
Approaches to Estimation

3. Use Z exogenous variation in exposure to the treatment T that does not affect outcome directly
   - *Instrumental variables*
   - *Natural quasi-experiments*
   - *Regression discontinuity design*

Approaches to Estimation

4. Identification through mechanisms. Estimates effect of treatment on mechanism and then mechanism on outcome
   - *Ferraro and Hanauer: T is protected area status and Y is poverty. M's are (a) ecotourism, (b) ecosystem services (improved), (c) restrictions on land use, (d) infrastructure.*
   - *Effect of air pollution on health and then plant emissions on air pollution*

Schematic



Issues (X and U)

- Selection bias
- Confounding factors
- Rival explanation
  - Protected area established in high elevation areas
  - Air pollution controls established in areas shutting down heavy manufacturing
  - Can also be an effect in the control
- Treatment Heterogeneity
  - If treatment only works in some (unknown) circumstances, the results are less useful

Treatment Estimates of Indonesian Parks

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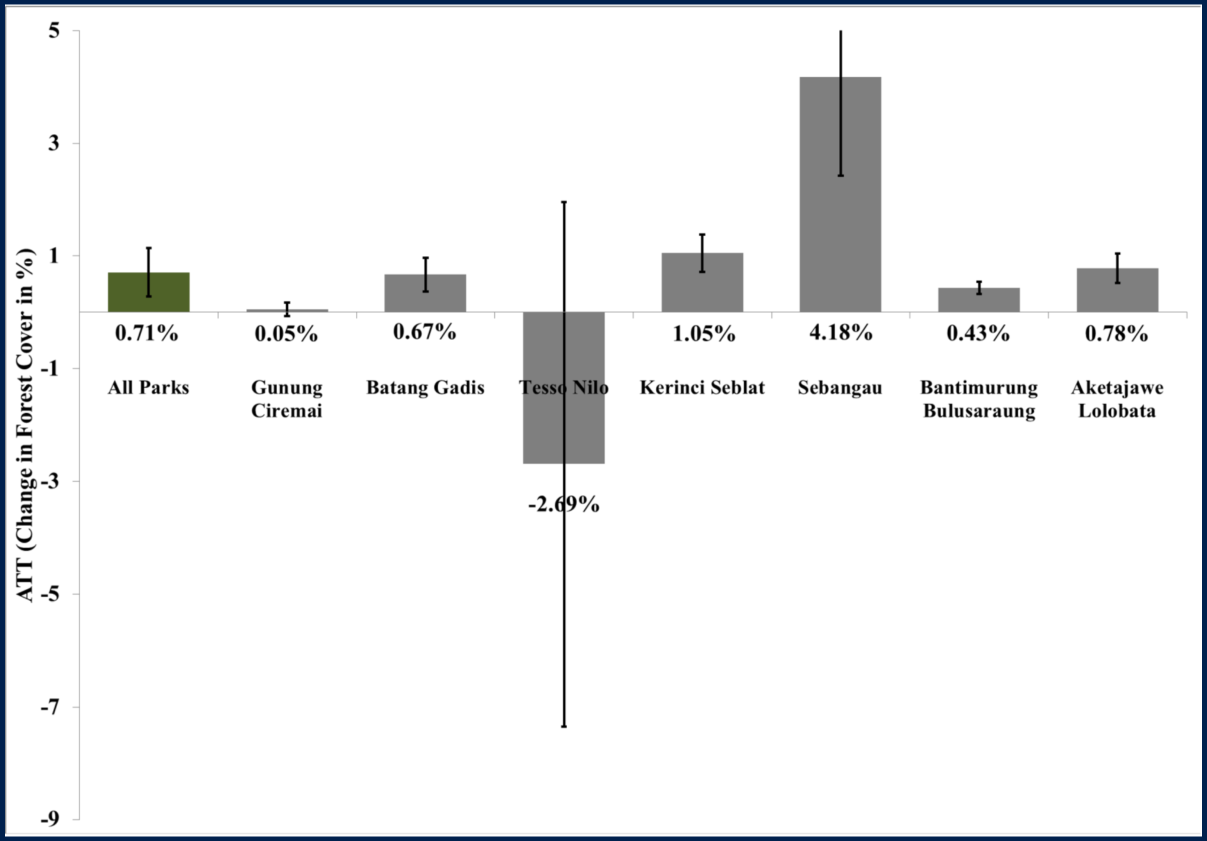

Implementing an Impact Assessment

So What Can We Do?

- Integrate Evaluation into Program Design
- Get Baseline Data!
- Systematically rule out alternatives

Rule Out Alternative Explanations

2	4	8

http://www.nytimes.com/interactive/2015/07/03/upshot/a-quick-puzzle-to-test-your-problem-solving.html

Programs Can Cause Their Own Problems

- Spillover or leakage
  - E.g. Forestry
  - E.g. livestock
- Effect of being observed
  - Hawthorne Effect
  - John Henry Effect
  - Pygmalion and Golum effect
  - E.g. monitoring experiment; CT vs CCT
- Anticipatory Effect
  - Change in behaviour induced by potential program introduction

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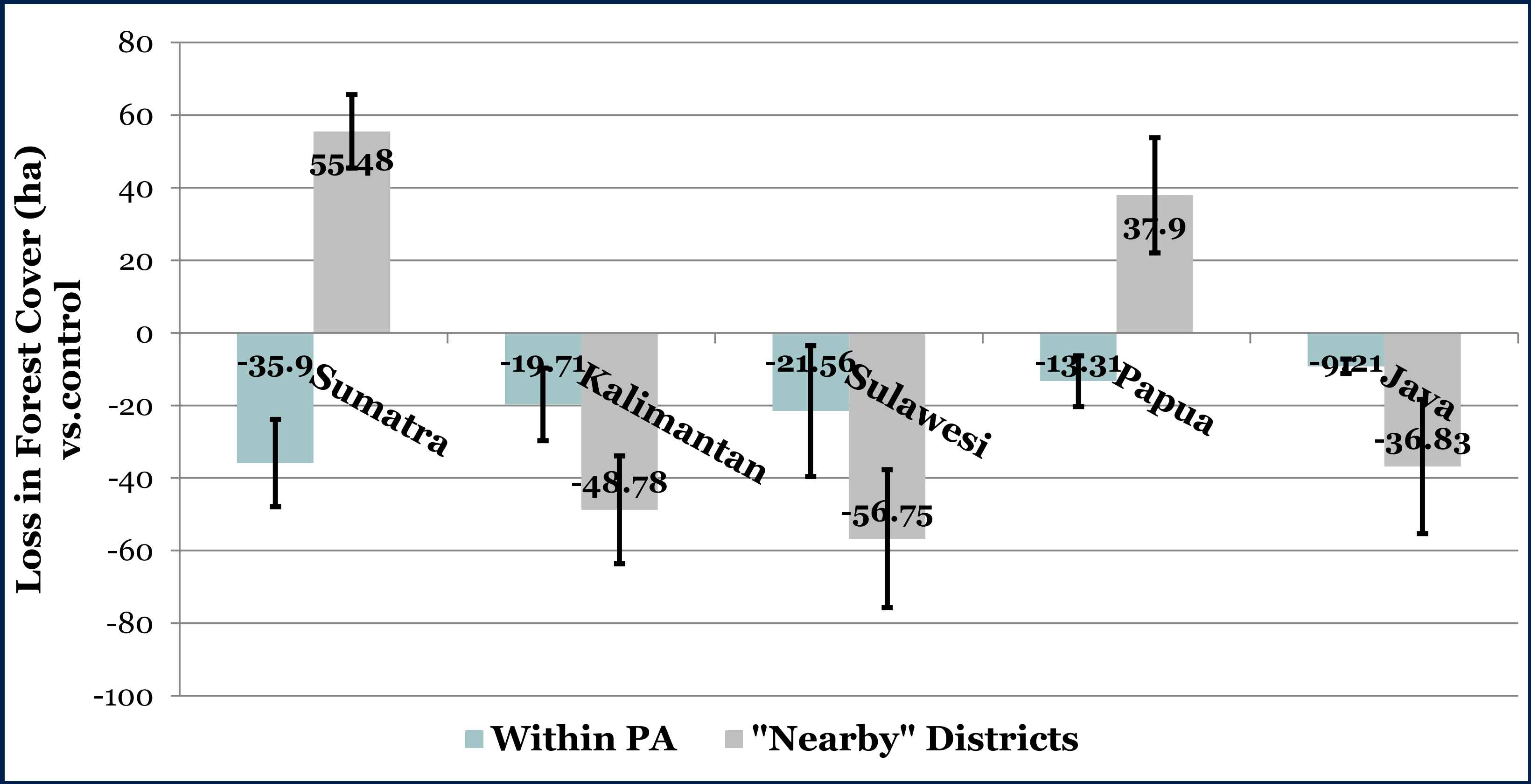
An Example: Deforestation



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Validity

- Internal validity (causal relationship)
- Construct validity (measuring treatment and outcome one reports)
- External validity (would the results be the same in another place/time?)

OK, Now You've Done Every Test…

- How much did it cost?
- Per acre/species/ecosystem service preserved?

Critique: Deaton (2009)

- Important question is not 'if it works' but 'why (or when and where) it works'
- Tests of theory versus test of programs (help with external validity)

Solutions

- Randomize T
- Match based on X
- IV (use Z)
- Quasi-experiments, RDD (using Z)
- Use Panel Methods to control for U

Rule out alternative explanations