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AT URBANA-CHAMPAIGN

Using Panel (aka Longitudinal) Data Estimators to Identify Causal Effects

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Outline for the Session

1. The Omitted Variables Problem (OVP)
2. Different panel estimators
3. Attrition and unbalanced panels
4. The art of the possible…
5. SUTVA Violations: Spillovers and Network Effects

The Omitted Variables Problem

The Omitted Variable Problem (OVP)

- Causal inference is a missing variables or omitted variables problem
  - We don't know what happened to those treated in the absence of the treatment
- RCTs solves the OVP by ensuring treatment and control groups are equivalent through randomization
  - We then assume the control group is representative of what would have happened to the treatment group had they not been treated

The Omitted Variable Problem (OVP)

- Matching solves the OVP by constructing a control group based on observable characteristics
  - Conditional on observables the matched group is representative of what would have happened to the treatment group had they not been treated
  - But this does not control for unobservables

The Omitted Variable Problem (OVP)

- IVs solve the OVP by assuming that there are unobservable differences between treatment and control and finding an instrument to break the correlation between the treatment and the unobservable differences
  - Conditional on a set of Identifying Assumptions the IV allows us to control for unobserved characteristics that make the treatment and control groups different and affect the outcome

The Omitted Variable Problem (OVP)

- Panel data techniques provide an additional way to try and establish causal inference
  - When we have multiple observations of plots/households/firms over time we can control for time invariant unobservables and common shocks to obtain consistent and unbiased estimates of the treatment effect

Some Preliminary Assumptions

- Assume a large population of cross-sectional units (plot, household, firm) that we can observe over time
- We randomly sample from the cross-section, so observations are necessarily independent in the cross-section
- We have a large cross-section (n) and relatively few time periods (t)

Some Preliminary Assumptions

- An individual-specific time-invariant unobservable, c_i, is drawn along with the observed data
  - *E.g. unobserved characteristics that affect probability of adoption, or for yield to be always better for one farmer than another.*
- Common shock, τ_t
  - *Prices, el nino.*

$$Y_{it} = \alpha X_{it} + \beta T_{it} + c_i + \tau_t + \epsilon_{it}$$

Some Preliminary Assumptions

$$Y_{it} = \alpha X_{it} + \beta T_{it} + c_i + \tau_t + \epsilon_{it}$$

- X_{it} is a set of observed variables that may combine variables that vary only over time (market price), over individual (soils) or both (weather).
- ϵ_{it} are the idiosyncratic errors
  - The composite error term is $v_{it} = c_i + \tau_t + \epsilon_{it}$
  - v_{it} is almost certainly serially correlated and definitely is if ϵ_{it} is serially uncorrelated. This will be because the value of c_i is the same for all t

Discussion: Irrigation Project Example

$$\log(income) = \alpha + \beta_1 Irrig_{it} + \beta_2 \log(dist_i) + c_i + \tau_t + \epsilon_{it}$$

- $Irrig_{it}$ is the treatment, if the households had received the irrigation project
- $dist_i$ is household distance to market and does not change over time

Discussion: Irrigation Project Example

$$\log(income) \\ = \alpha + \beta_1 Irrig_{it} + \beta_2 \log(dist_i) + c_i + \tau_t + \epsilon_{it}$$

- We are interested in effects of irrigation. Distance is just a control for cost of transporting the good
  - Are there time constant differences between households not captured by distance?

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YES

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    YES

  - Are those factors, in c_i, correlated with $Irrig_{it}$?

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YES

  - Are those factors, in c_i, correlated with $Irrig_{it}$?

Probably

Different Panel Data Models

Panel Data Models

- Primary focus will be on the following
  - Pooled Ordinary Least Squares (OLS)
  - Random Effects (RE)
  - Fixed Effects (FE)
  - Correlated Random Effects (CRE)
- Alternative models
  - First Differencing (FD)
  - Multilevel Model (MLM)

Pooled OLS

- Assumes $Cov(v_{it}, v_{is}) = 0$ and $Cov(v_{it}, v_{jt}) = 0$
  - In words: the composite error term is uncorrelated across time (no serial correlation).
  - And across individuals (and treatment groups)
  - This will clearly not be true if there are time-invariant unobserved effects in our model or group effects
- How likely is it that there are no unobserved effects in our model?
  - Back to the U's

Pooled OLS

- Using OLS estimate

$$Y_{it} = \alpha + \delta R_i + \gamma X_{it} + c_i + \tau_t + \epsilon_{it}$$

- To test if the errors are serially uncorrelated, save $\hat{\epsilon}_{it}$ and then regress
  - $\hat{\epsilon}_{it} = \rho\hat{\epsilon}_{it-1} + u_t$
  - If $\rho = 0$ then errors are serially uncorrelated and Pooled OLS is BLUE
  - If $\rho \neq 0$ then errors are serially correlated and you need a panel data estimator

Random Effects

- Assumes $Cov(X_{it}, c_i) = 0$
  - Alternatively, $E[c_i|X_{it}] = E[c_i]$ – conditional mean independence
  - In words: the unobserved effect is uncorrelated with the observed explanatory variables
- How likely is it that unobserved individual characteristics are uncorrelated with observed characteristics?
  - Isn't the whole point of using panel data to allow for c_i to be arbitrarily correlated with X_{it}?

Random Effects

- Using GLS estimate

$$Y_{it} = \alpha + \delta R_i + \gamma X_{it} + v_{it}$$

- Several tests for validity of REs
  - To test if $c_i = 0$ you can use the Breusch-Pagan Lagrangian multiplier test for RE
  - To test if the unobserved effect is uncorrelated with the observed explanatory variables we can use a Hausman Test

Fixed Effects

- Allows for $Cov(X_{it}, c_i) \neq 0$
  - Alternatively, $E[c_i|X_{it}]$ is allowed to be any value
  - In words: allows for arbitrary correlation between unobserved effect and the observed explanatory variables
  - Explicitly estimate c_i and/or τ_i
- Equivalent to 'de-meaning' the data in a linear model
- But, panel FE does not allow us to simultaneously estimate time-constant variables
  - Can back them out in a secondary regression:

$$\hat{c}_i = \alpha + \gamma X_i + \mu_i$$

Fixed Effects

- estimate

$$Y_{it} = \gamma X_{it} + \zeta c_i + \theta \tau_t + \epsilon_{it}$$

- Include binary indicators for each individual
  - Note this controls for c_i but removes R_i due to perfect collinearity

Correlated Random Effects

- Assumes $E[c_i|X_{it}] = E[c_i|\bar{X}_i] = \psi + \xi\bar{X}_i$
  - In words: we model the dependence between unobserved effect and the observed explanatory variables as

$$c_i = \psi + \xi\bar{X}_i + a_i$$

- Allows us to unify FE and RE estimation approaches

Correlated Random Effects

- First, define the relationship between the unobserved effect and the observed covariates

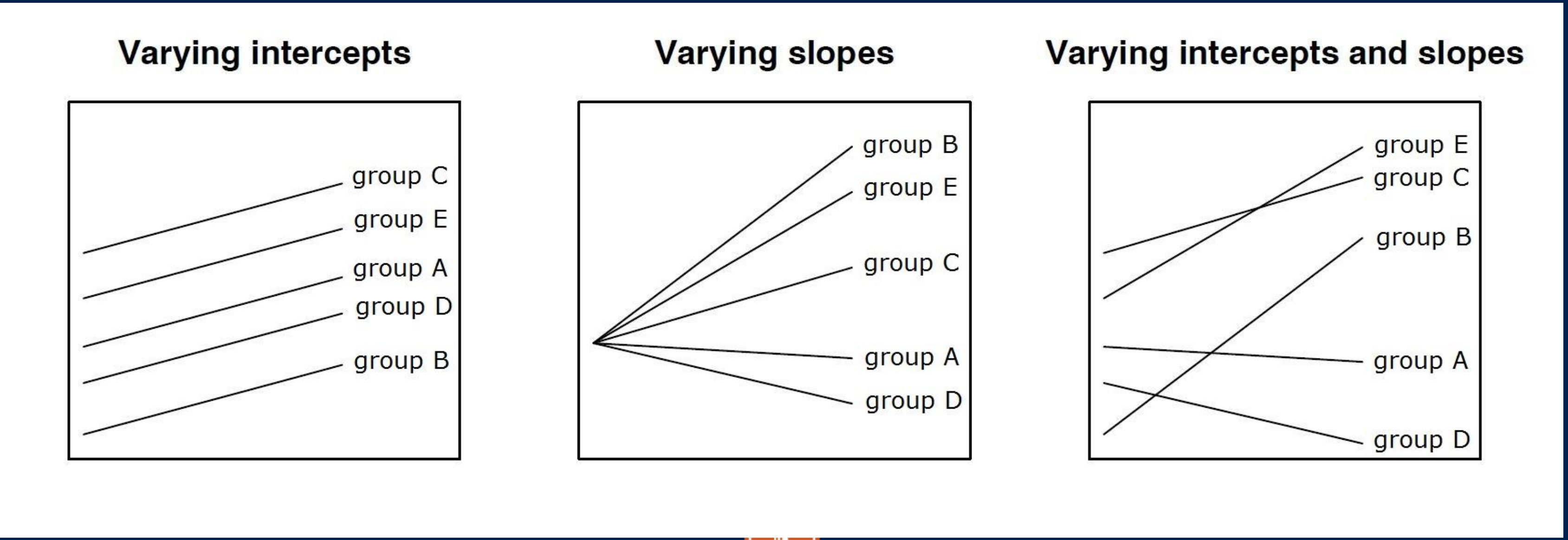
$$c_i = \psi + \xi \bar{X}_i + a_i$$

- Second, estimate the equation with OLS

$$Y_{it} = \theta G_t + \delta R_i + \gamma X_{it} + \psi + \xi \bar{X}_i + a_i + \epsilon_{it}$$

How many FE should we include?

- Individual or Group FE
- Time
- Group x time



Where is our variation coming from?

Year	a	b	c	d	Ave
1	100	120	110	140	117.5
2	110	135	105	155	125
3	85	90	100	110	96.25
4	150	140	95	145	133.75
Ave	110	122.5	102.5	137.5	

OLS – variation between households and over time

With year FE

Year	a	b	c	d	Ave
1	100 [-17.5]	120 [2.5]	110 [-7.5]	140 [22.5]	117.5
2	110 [-15]	135 [-10]	105 [-20]	155 [25]	125
3	85 [-16.25]	90 [-6.25]	100 [3.75]	110 [13.75]	96.25
4	150 [16.25]	140 [6.25]	95 [-38.75]	145 [12.25]	133.75
Ave	110	122.5	102.5	137.5	

Difference among households within year

Common shocks (e.g. world price; el nino)

With HH FE?

Year	a	b	c	d	Ave
1	100 [-10]	120 [-2.5]	110 [-7.5]	140 [2.5]	117.5
2	110 [0]	135 [22.5]	105 [2.5]	155 [17.5]	125
3	85 [-25]	90 [-32.5]	100 [2.5]	110 [-27.5]	96.25
4	150 [40]	140 [27.5]	95 [-7.5]	145 [7.5]	133.75
Ave	110	122.5	102.5	137.5	

Household-specific effects (soil type, education, farm size)

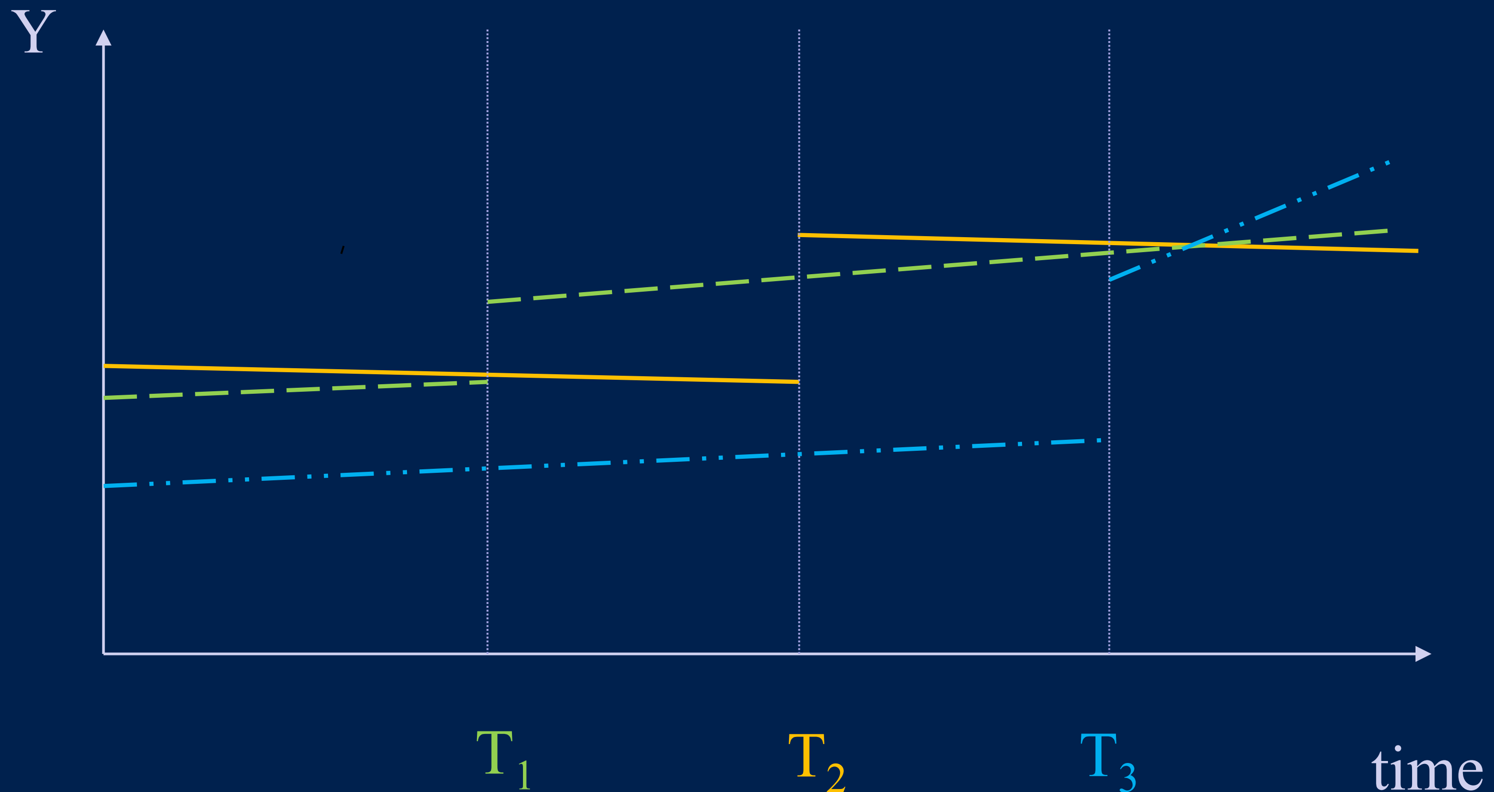
Now comparing households to themselves over time

With group time trends?

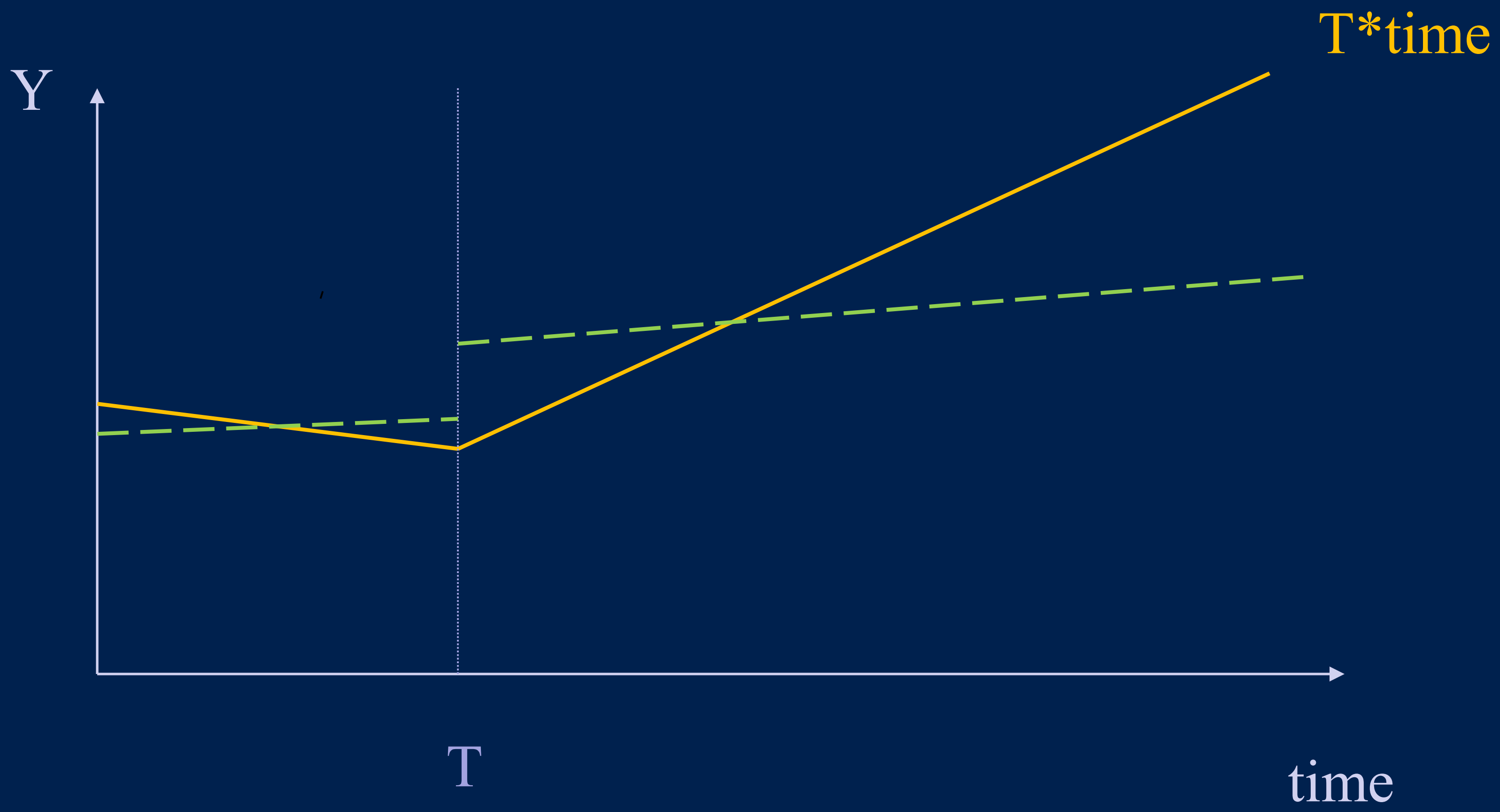
Year	a	b	c	d	Ave
1	100 [-10]	120 [-2.5]	110 [-7.5]	140 [2.5]	117.5
2	110 [0]	135 [22.5]	105 [2.5]	155 [17.5]	125
3	85 [-25]	90 [-32.5]	100 [2.5]	110 [-27.5]	96.25
4	150 [40]	140 [27.5]	95 [-7.5]	145 [7.5]	133.75
Ave	110	122.5	102.5	137.5	

Now comparing household deviation from group trend

Treatment over time



What if treatment affects trajectory, not level?



Attrition

Practical issue when collecting longitudinal (panel) data.

- Some households will be away, some will have a different respondent
- Some households will have migrated
- Some will no longer want to participate

Check %, check whether missing observations are systematically different from folks staying

Collect data on new households to preserve geographic sample

-> *Unbalanced Panel Methods*

The Art of the Possible…

So you don't have baseline data…

- Recall?
- Secondary data? (national surveys; satellite imagery)

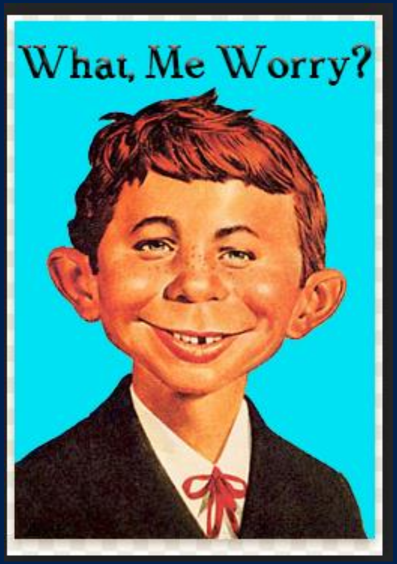
So you don't have data on controls…

- Variation in treatment intensity?
- Variation in treatment timing?

In general

- Placebo tests – rule out other options (informed by theory of change)
- Qualitative data to rule out other options

SUTVA Violations



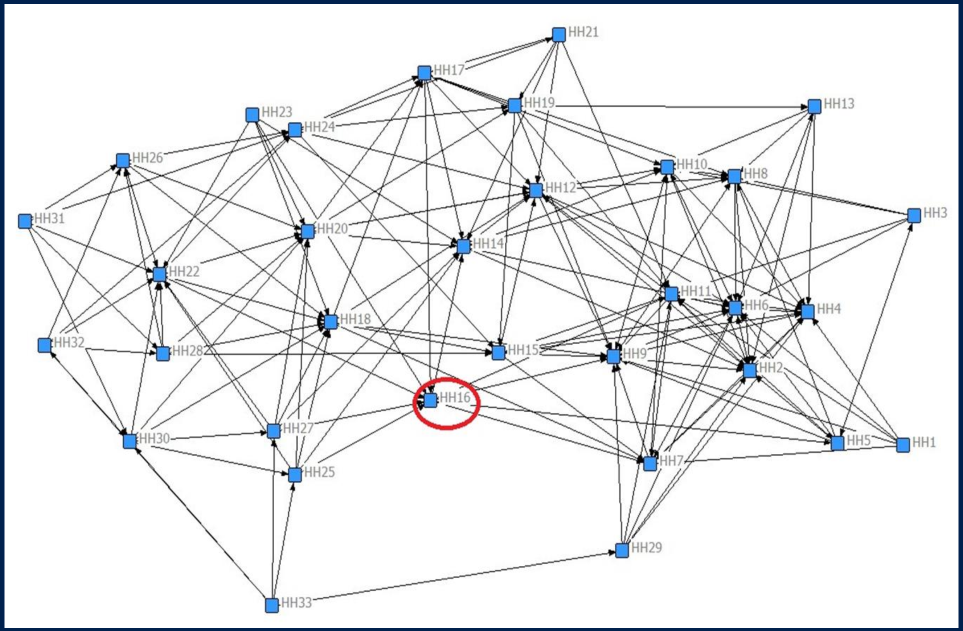
Spillovers (when SUTVA falls apart…)

- Social Networks
- Peer Effects
- Group threshold Effects
- Spatial Spillovers

- *Bias estimated treatment effects*
- *Often important in and of themselves*
- *Ideally integrate into research design*

Social Network Effects

- Where a program is placed within a social network matters
- Banerjee et al (2011) – microfinance in India
- Songersemsawas et al (2015) – contract choice



Peer Effects

- Reflection Problem
- Can solve through using characteristics of friends of friends as instruments
- Do peer effects through social networks affect…
  - Input use in new crops (Conley and Udry 2010)
  - Land allocation to new crops (Munshi 2004)
  - Market mechanisms (Fafchamps and Minton 1998, 1999, 2002; Michelson 2015)
  - Agricultural revenue (Songsermsawas et al 2015b)

Mechanism?

- Influence versus Information (Montgomery and Casterline)
- Oster and Thornton (2012)
  - *Wanting to do like friends?*
  - *Switching behavior because of friends' positive benefits?*
  - *Learning how to use a new technology*

Within village spillovers and threshold effects

Within Village Spillovers

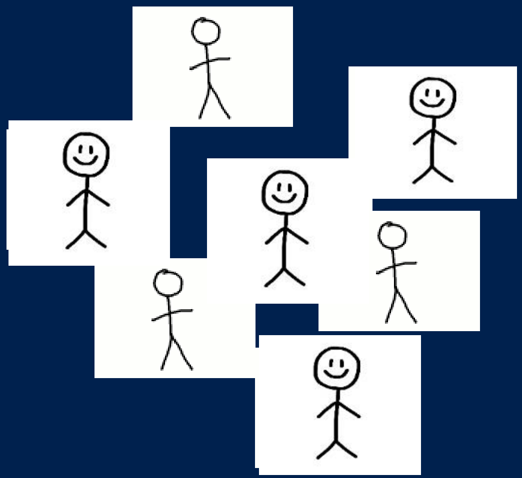
- Can identify through different intensity of treatment (Baird et al 2015)
- Can identify through modeling peer networks

Threshold Effects

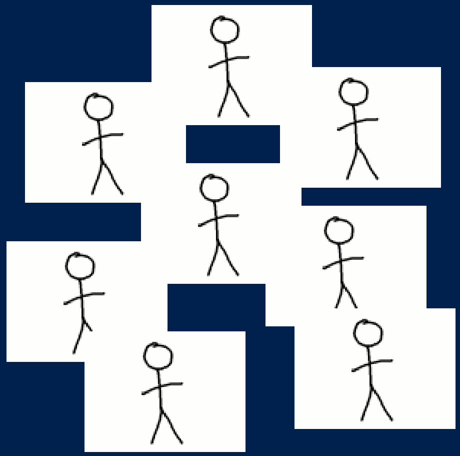
- Idea that an intervention needs to reach a certain saturation point to have an effect

example

- Only some people eligible



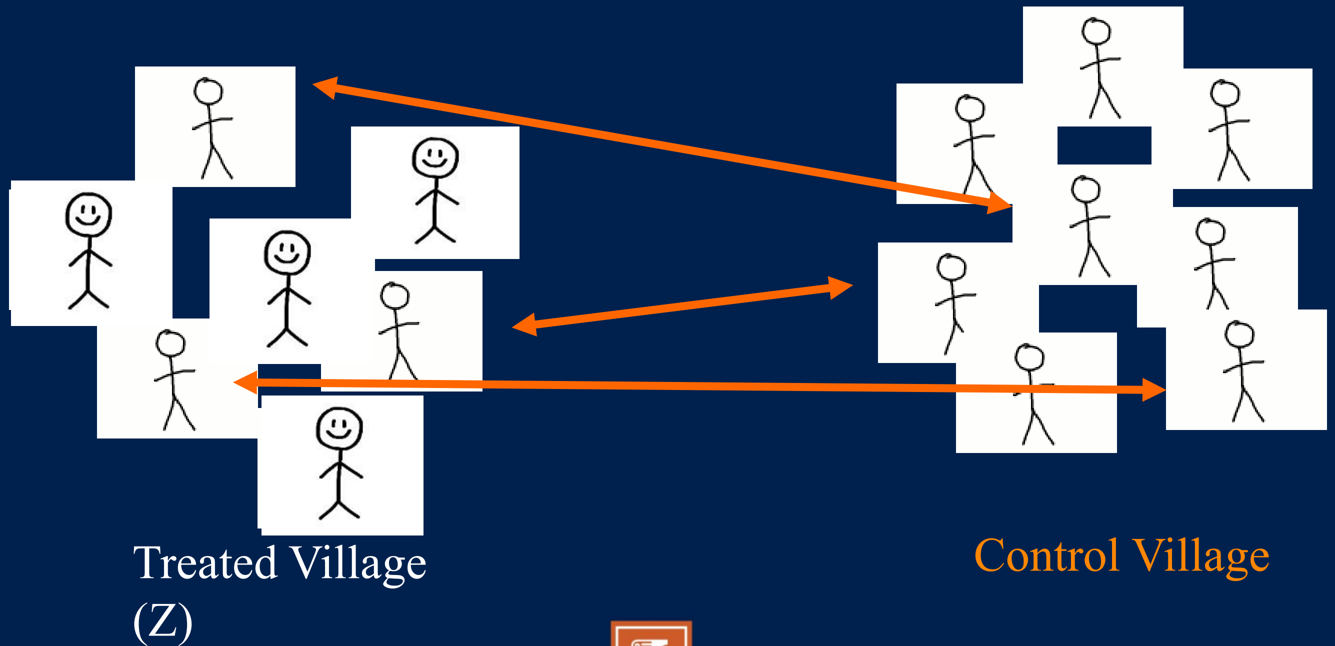
Treated Village
(Z)



Control Village

example

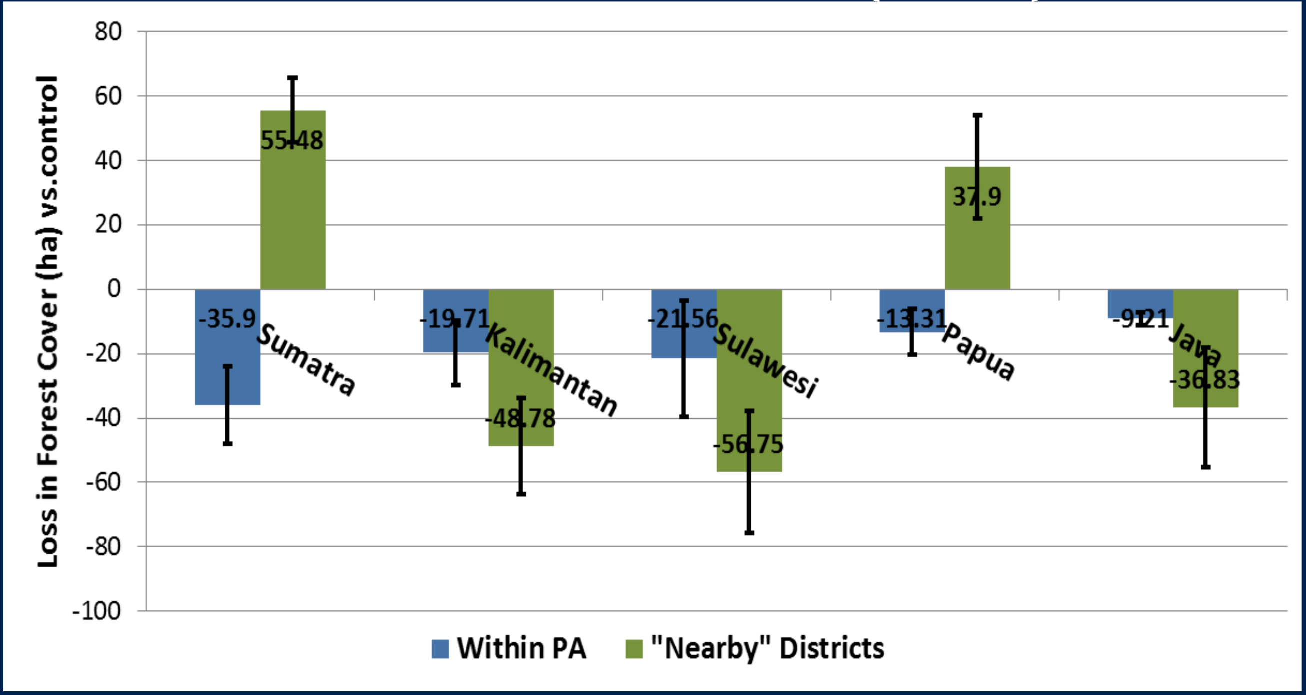
- Only some people eligible: compare ineligible people to controls



Between Villages: Even if one randomizes....

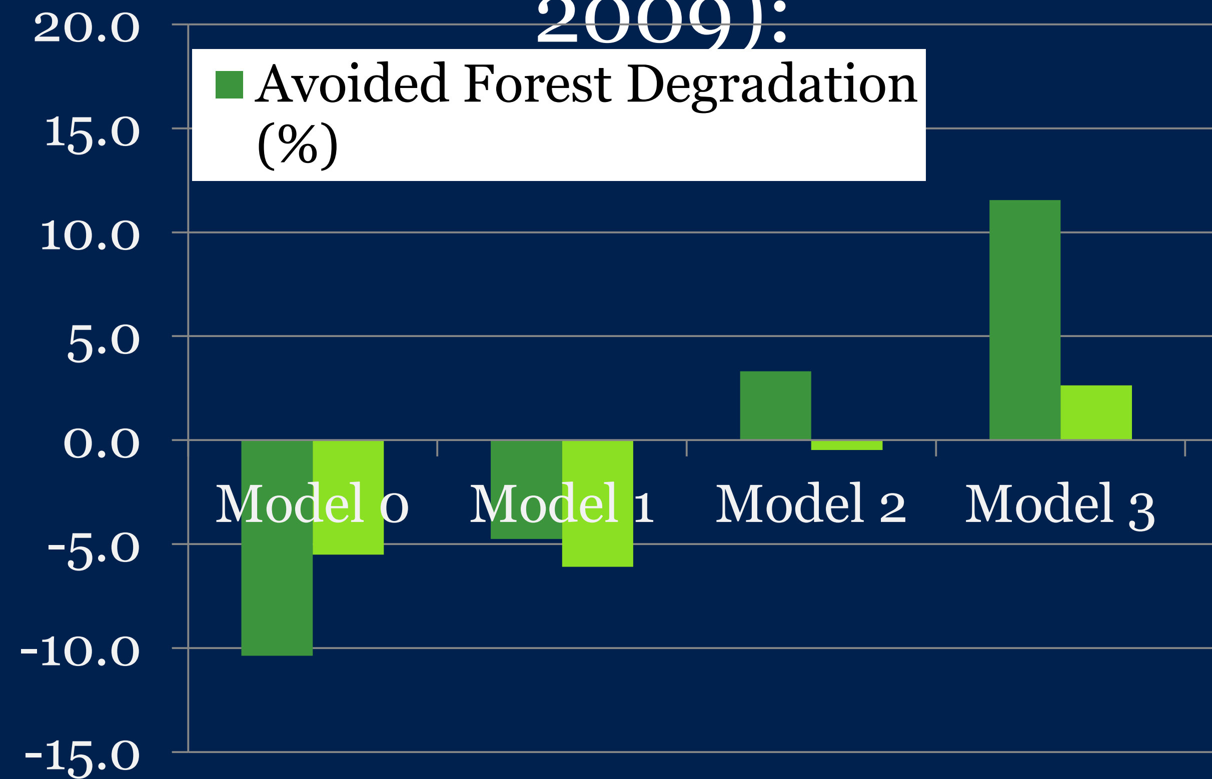
	Spatial Correlation Parameter					
	0.00	0.10	0.25	0.50	0.75	0.90
DD						
% Bias	-0.9	1.2	3.3	21.2	83.0	282.4
Rejection rate (95% Conf.)	93.4	94.5	92.1	86.0	68.1	50.2
DD with village fixed-effects						
% Bias	-0.9	1.2	3.3	21.2	83.0	282.4
Rejection rate (95% Conf.)	93.2	94.3	92.0	85.9	68.1	50.1
DD with individual fixed-effects						
% Bias	-0.9	1.2	3.3	21.2	83.0	282.4
Rejection rate (95% Conf.)	75.6	77.4	73.8	61.4	35.7	18.5
Spatial AR-DD						
% Bias	-0.9	0.7	-0.8	-0.2	0.3	0.2
Rejection rate (95% Conf.)	93.6	94.7	92.7	93.9	93.2	94.2

Spillovers: Forest Leakage from Protected Areas (PAs)



- Model 0: DiD, FE
- Model 1: DiD with Matching
- Model 2: DiD with Spatial Matching
- Model 3: Removing neighbouring controls

Avoided forest loss (1993 vs 2009):



Even without explicit spillovers…

- Error terms across neighbouring observations may be correlated
  - E.g. plot level data correlated by household
  - All households in a village being treated
  - Clustering standard errors

Spatially-correlated errors

	Spatial Correlation Parameter					
	0.00	0.10	0.25	0.50	0.75	0.90
DD						
% Bias	-0.1	-0.9	-0.6	-1.2	-0.6	4.4
Rejection rate (95% Conf.)	87.1	86.8	86.2	80.6	57.7	19.1
DD with village fixed-effects						
% Bias	-0.1	-0.9	-0.6	-1.2	-0.6	4.4
Rejection rate (95% Conf.)	87.0	86.5	86.0	80.6	57.7	19.1
DD with individual fixed-effects						
% Bias	-0.1	-0.9	-0.6	-1.2	-0.6	4.4
Rejection rate (95% Conf.)	64.6	65.3	62.6	54.1	25.4	4.9
Spatial Error-DD						
% Bias	-0.1	-0.9	-0.5	-1.1	-0.1	1.9
Rejection rate (95% Conf.)	87.7	86.6	87.1	83.0	78.6	76.2

Summary about SUTVA

- Set experimental design to minimize SUTVA

or…

- Build spillovers into the evaluation
- The spillovers may be interesting in and of themselves