When Should We Use Linear Fixed Effects Regression Models for Causal Inference with Longitudinal Data?

Kosuke Imai

Department of Politics
Center for Statistics and Machine Learning
Princeton University

Joint work with In Song Kim (MIT)

Seminar at Yokohama City University
June 24, 2016

Fixed Effects Regressions in Causal Inference

- Linear fixed effects regression models are the primary workhorse for causal inference with longitudinal/panel data
- Researchers use them to adjust for unobserved time-invariant confounders (omitted variables, endogeneity, selection bias, ...):
  - "Good instruments are hard to find ..., so we'd like to have other tools to deal with unobserved confounders. This chapter considers ... strategies that use data with a time or cohort dimension to control for unobserved but fixed omitted variables" (Angrist & Pischke, *Mostly Harmless Econometrics*)
  - "fixed effects regression can scarcely be faulted for being the bearer of bad tidings" (Green *et al.*, *Dirty Pool*)

Overview of the Talk

- Identify two under-appreciated causal assumptions of unit fixed effects regression estimators:
  1. Past treatments do not directly affect current outcome
  2. Past outcomes do not directly affect current treatments and time-varying confounders

  $\rightsquigarrow$ can be relaxed under a selection-on-observables approach

- A New matching framework for causal inference with panel data:
  1. develop within-unit matching estimators to relax linearity
  2. incorporate design-based identification strategies such as the before-and-after and difference-in-differences designs
  3. establish equivalence between matching estimators and weighted linear fixed effects estimators

- An empirical illustration: Effects of GATT on trade

Linear Regression with Unit Fixed Effects

- Balanced panel data with N units and T time periods
- Y_{it}: outcome variable
- X_{it}: causal or treatment variable of interest

Assumption 1 (Linearity)

$$Y_{it} \; = \; \alpha_i + \beta X_{it} + \epsilon_{it}$$

- $\mathbf{U}_i$: a vector of unobserved time-invariant confounders
- $\alpha_i = h(\mathbf{U}_i)$ for *any* function $h(\cdot)$
- A flexible way to adjust for unobservables
- Average contemporaneous treatment effect:

$$\beta \; = \; \mathbb{E}(Y_{it}(1) - Y_{it}(0))$$

Strict Exogeneity and Least Squares Estimator

Assumption 2 (Strict Exogeneity)

$$\epsilon_{it} \perp\!\!\!\perp \{\mathbf{X}_i, \mathbf{U}_i\}$$

- Mean independence is sufficient: $\mathbb{E}(\epsilon_{it} \mid \mathbf{X}_i, \mathbf{U}_i) = \mathbb{E}(\epsilon_{it}) = 0$
- Least squares estimator based on de-meaning:

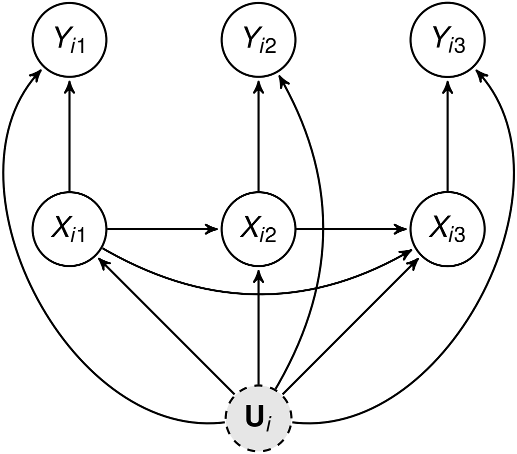
$$\hat{\beta}_{\text{FE}} = \underset{\beta}{\arg\min} \sum_{i=1}^{N} \sum_{t=1}^{T} \{(Y_{it} - \overline{Y}_i) - \beta(X_{it} - \overline{X}_i)\}^2$$

  where $\overline{X}_i$ and $\overline{Y}_i$ are unit-specific sample means
- ATE among those units with variation in treatment:

$$\tau = \mathbb{E}(Y_{it}(1) - Y_{it}(0) \mid C_{it} = 1)$$

  where $C_{it} = \mathbf{1}\{0 < \sum_{t=1}^{T} X_{it} < T\}$.

Causal Directed Acyclic Graph (DAG)



- arrow $=$ direct causal effect
- absence of arrows $\rightsquigarrow$ causal assumptions

Nonparametric Structural Equation Model (NPSEM)

- One-to-one correspondence with a DAG:

$$\begin{aligned} Y_{it} &= g_1(X_{it}, \mathbf{U}_i, \epsilon_{it}) \\ X_{it} &= g_2(X_{i1}, \ldots, X_{i,t-1}, \mathbf{U}_i, \eta_{it}) \end{aligned}$$

- Nonparametric generalization of linear unit fixed effects model:
  - Allows for nonlinear relationships, effect heterogeneity
  - Strict exogeneity holds
  - No arrows can be added without violating Assumptions 1 and 2
- Causal assumptions:
  1. No unobserved time-varying confounders
  2. Past outcomes do not directly affect current outcome
  3. Past outcomes do not directly affect current treatment
  4. Past treatments do not directly affect current outcome

Potential Outcomes Framework

- DAG $\rightsquigarrow$ causal structure
- Potential outcomes $\rightsquigarrow$ treatment assignment mechanism

Assumption 3 (No carryover effect)

Past treatments do not directly affect current outcome

$$Y_{it}(X_{i1}, X_{i2}, \ldots, X_{i,t-1}, X_{it}) \;=\; Y_{it}(X_{it})$$

- What randomized experiment satisfies unit fixed effects model?
  1. randomize X_{i1} given $\mathbf{U}_i$
  2. randomize X_{i2} given X_{i1} and $\mathbf{U}_i$
  3. randomize X_{i3} given X_{i2}, X_{i1}, and $\mathbf{U}_i$
  4. and so on

Assumption 4 (Sequential Ignorability with Unobservables)

$$\{Y_{it}(1), Y_{it}(0)\}_{t=1}^{T} \perp\!\!\!\perp X_{i1} \mid \mathbf{U}_i$$

$$\vdots$$

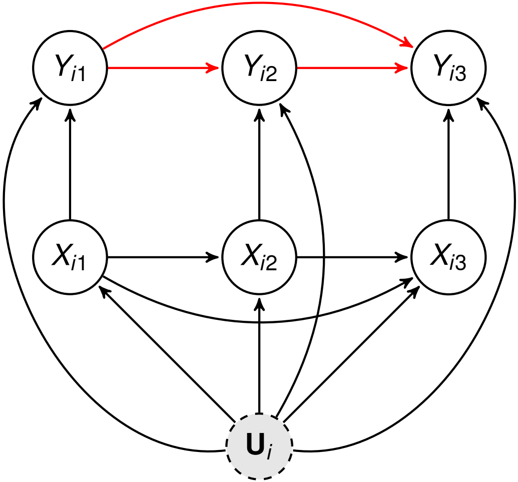
$$\{Y_{it}(1), Y_{it}(0)\}_{t=1}^{T} \perp\!\!\!\perp X_{it'} \mid X_{i1}, \ldots, X_{i,t'-1}, \mathbf{U}_i$$

$$\vdots$$

$$\{Y_{it}(1), Y_{it}(0)\}_{t=1}^{T} \perp\!\!\!\perp X_{iT} \mid X_{i1}, \ldots, X_{i,T-1}, \mathbf{U}_i$$

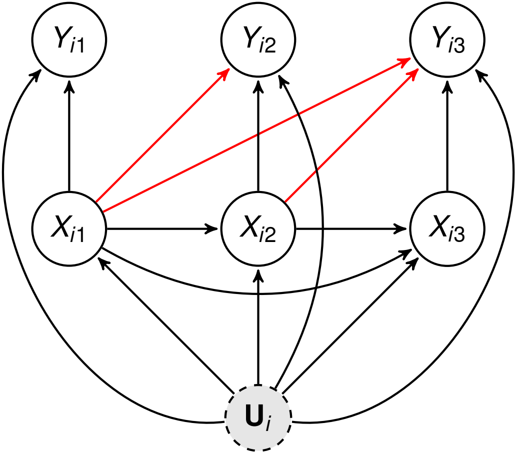
- "as-if random" assumption without conditioning on past outcomes
- Past outcomes cannot directly affect current treatment
- Says nothing about whether past outcomes can directly affect current outcome

Past Outcomes Directly Affect Current Outcome



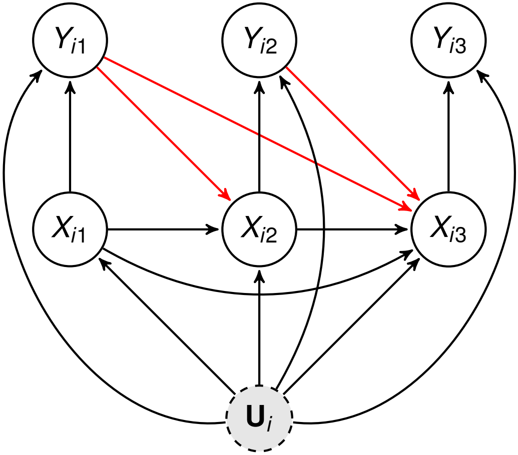
- Strict exogeneity still holds
- Past outcomes do not confound $X_{it} \longrightarrow Y_{it}$ given $\mathbf{U}_i$
- No need to adjust for past outcomes

Past Treatments Directly Affect Current Outcome



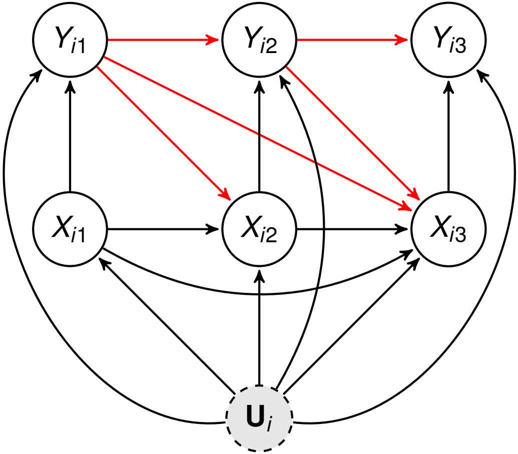
- Past treatments as confounders
- Need to adjust for past treatments
- Strict exogeneity holds given past treatments and $\mathbf{U}_i$
- Impossible to adjust for an entire treatment history and $\mathbf{U}_i$ at the same time
- Adjust for a small number of past treatments $\rightsquigarrow$ often arbitrary

Past Outcomes Directly Affect Current Treatment



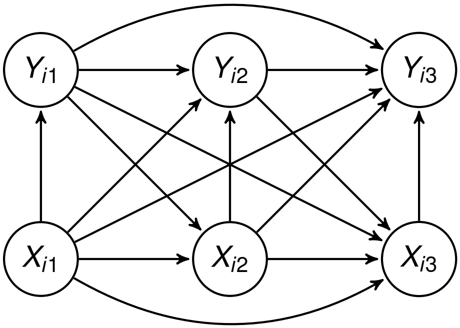
- Correlation between error term and future treatments
- Violation of strict exogeneity
- No adjustment is sufficient
- Together with the previous assumption $\rightsquigarrow$ no feedback effect over time

Instrumental Variables Approach



- Instruments: X_{i1}, X_{i2}, and Y_{i1}
- GMM: Arellano and Bond (1991)
- Exclusion restrictions
- Arbitrary choice of instruments
- Substantive justification rarely given

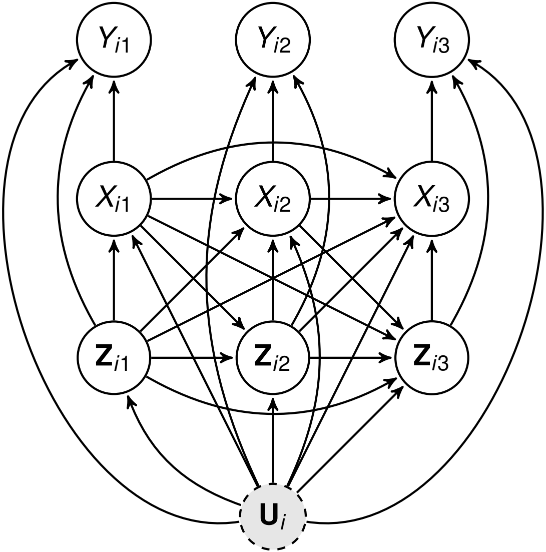
An Alternative Selection-on-Observables Approach



- Absence of unobserved time-invariant confounders $\mathbf{U}_i$
- past treatments can directly affect current outcome
- past outcomes can directly affect current treatment

- Comparison across units within the same time rather than across different time periods within the same unit
- Marginal structural models $\rightsquigarrow$ can identify the average effect of an entire treatment sequence
- Trade-off $\rightsquigarrow$ no free lunch

Adjusting for Observed Time-varying Confounders



- past treatments cannot directly affect current outcome
- past outcomes cannot directly affect current treatment
- adjusting for $\mathbf{Z}_{it}$ does not relax these assumptions
- past outcomes cannot *indirectly* affect current treatment through $\mathbf{Z}_{it}$

A New Matching Framework

- Even if these assumptions are satisfied, the the unit fixed effects estimator is inconsistent for the ATE:

$$\hat{\beta}_{\text{FE}} \xrightarrow{p} \frac{\mathbb{E}\left\{C_i\left(\frac{\sum_{t=1}^T X_{it}Y_{it}}{\sum_{t=1}^T X_{it}} - \frac{\sum_{t=1}^T (1-X_{it})Y_{it}}{\sum_{t=1}^T 1-X_{it}}\right)S_i^2\right\}}{\mathbb{E}(C_i S_i^2)} \neq \tau$$

  where $S_i^2 = \sum_{t=1}^T (X_{it} - \overline{X}_i)^2/(T-1)$ is the unit-specific variance

- Key idea: comparison across time periods within the same unit
- The Within-unit matching estimator improves $\hat{\beta}_{\text{FE}}$ by relaxing the linearity assumption:

$$\hat{\tau}_{\text{match}} = \frac{1}{\sum_{i=1}^N C_i}\sum_{i=1}^N C_i\left(\frac{\sum_{t=1}^T X_{it}Y_{it}}{\sum_{t=1}^T X_{it}} - \frac{\sum_{t=1}^T (1-X_{it})Y_{it}}{\sum_{t=1}^T (1-X_{it})}\right)$$

Constructing a General Matching Estimator

- $\mathcal{M}_{it}$: matched set for observation (i, t)
- For the within-unit matching estimator,

$$\mathcal{M}_{it}^{\text{match}} = \{(i', t') : i' = i, X_{i't'} = 1 - X_{it}\}$$

- A general matching estimator:

$$\hat{\tau}_{\text{match}} = \frac{1}{\sum_{i=1}^{N} \sum_{t=1}^{T} D_{it}} \sum_{i=1}^{N} \sum_{t=1}^{T} D_{it}(\widehat{Y_{it}(1)} - \widehat{Y_{it}(0)})$$

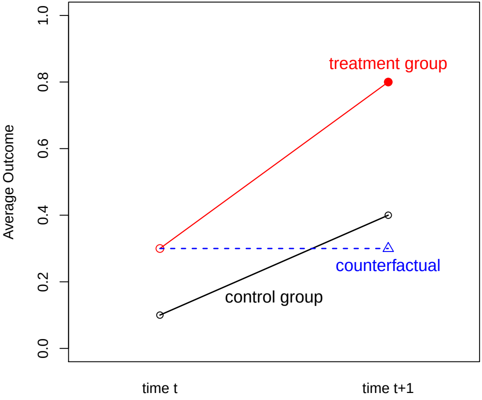
where $D_{it} = \mathbf{1}\{\#\mathcal{M}_{it} > 0\}$ and

$$\widehat{Y_{it}(x)} = \begin{cases} Y_{it} & \text{if } X_{it} = x \\ \frac{1}{\#\mathcal{M}_{it}} \sum_{(i',t') \in \mathcal{M}_{it}} Y_{i't'} & \text{if } X_{it} = 1 - x \end{cases}$$

Before-and-After Design

- Assumed absence of feedback effects may not be credible
- Use an alternative assumption about time trend rather than treatment assignment:

$$\mathbb{E}(Y_{it}(x) \mid X_{it} = x', \mathbf{U}_i) \quad = \quad \mathbb{E}(Y_{i,t-1}(x) \mid X_{i,t-1} = 1 - x', \mathbf{U}_i)$$



- no time trend for the average potential outcomes
- $x = 0$ and $x' = 1$: assumption made for control outcome only

- This is a matching estimator with the following matched set:

$$\mathcal{M}_{it}^{BA} = \{(i', t') : i' = i, t' \in \{t-1, t+1\}, X_{i't'} = 1 - X_{it}\}$$

- It is also the first differencing estimator:

$$\hat{\beta}_{\text{FD}} = \arg\min_{\beta} \sum_{i=1}^{N} \sum_{t=2}^{T} \{(Y_{it} - Y_{i,t-1}) - \beta(X_{it} - X_{i,t-1})\}^2$$

- “We emphasize that the model and the interpretation of β are *exactly* as in [the linear fixed effects model]. What differs is our method for estimating β” (Wooldridge; italics original).

- The identification assumptions is very different

Matching as a Weighted Unit Fixed Effects Estimator

- *Any* within-unit matching estimator can be written as a weighted unit fixed effects estimator with different regression weights
- The proposed within-matching estimator:

$$\hat{\beta}_{\text{WFE}} = \underset{\beta}{\arg\min} \sum_{i=1}^{N} \sum_{t=1}^{T} D_{it} W_{it} \{(Y_{it} - \overline{Y}_i^*) - \beta(X_{it} - \overline{X}_i^*)\}^2$$

where $\overline{X}_i^*$ and $\overline{Y}_i^*$ are unit-specific weighted averages, and

$$W_{it} = \begin{cases} \frac{T}{\sum_{t'=1}^{T} X_{it'}} & \text{if} \quad X_{it} = 1, \\ \frac{T}{\sum_{t'=1}^{T} (1 - X_{it'})} & \text{if} \quad X_{it} = 0. \end{cases}$$

- We show how to construct regression weights for different matching estimators (i.e., different matched sets)
- Idea: count the number of times each observation is used for matching

- Benefits:
  - computational efficiency
  - model-based standard errors
  - robustness $\rightsquigarrow$ matching estimator is consistent even when linear unit fixed effects regression is the true model
  - specification test (White 1980) $\rightsquigarrow$ null hypothesis: linear fixed effects regression is the true model

Linear Regression with Unit and Time Fixed Effects

- Model:

$$Y_{it} = \alpha_i + \gamma_t + \beta X_{it} + \epsilon_{it}$$

where γ_t flexibly adjusts for a vector of unobserved unit-invariant time effects $\mathbf{V}_t$, i.e., $\gamma_t = f(\mathbf{V}_t)$

- Estimator:

$$\hat{\beta}_{\text{FE2}} = \arg\min_{\beta} \sum_{i=1}^{N} \sum_{t=1}^{T} \{(Y_{it} - \overline{Y}_i - \overline{Y}_t + \overline{Y}) - \beta(X_{it} - \overline{X}_i - \overline{X}_t + \overline{X})\}^2$$

where $\overline{Y}_t$ and $\overline{X}_t$ are time-specific means, and $\overline{Y}$ and $\overline{X}$ are overall means

Understanding the Two-way Fixed Effects Estimator

- β_{FE}: bias due to time effects
- β_{FEtime}: bias due to unit effects
- β_{pool}: bias due to both time and unit effects

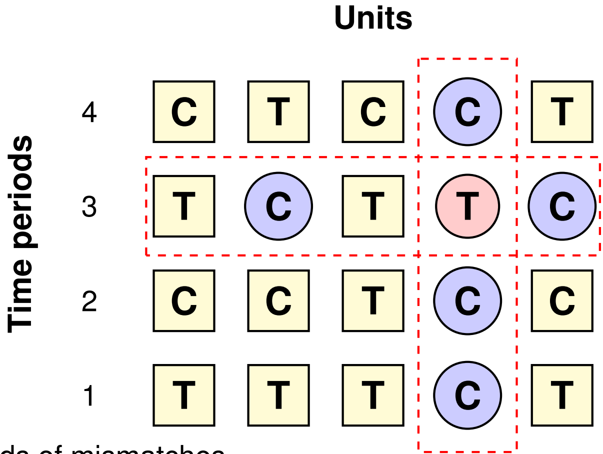
$$\hat{\beta}_{\text{FE2}} = \frac{\omega_{\text{FE}} \times \hat{\beta}_{\text{FE}} + \omega_{\text{FEtime}} \times \hat{\beta}_{\text{FEtime}} - \omega_{\text{pool}} \times \hat{\beta}_{\text{pool}}}{w_{\text{FE}} + w_{\text{FEtime}} - w_{\text{pool}}}$$

with sufficiently large N and T, the weights are given by,

$$\begin{aligned} \omega_{\text{FE}} &\approx \mathbb{E}(S_i^2) = \text{average unit-specific variance} \\ \omega_{\text{FEtime}} &\approx \mathbb{E}(S_t^2) = \text{average time-specific variance} \\ \omega_{\text{pool}} &\approx S^2 = \text{overall variance} \end{aligned}$$

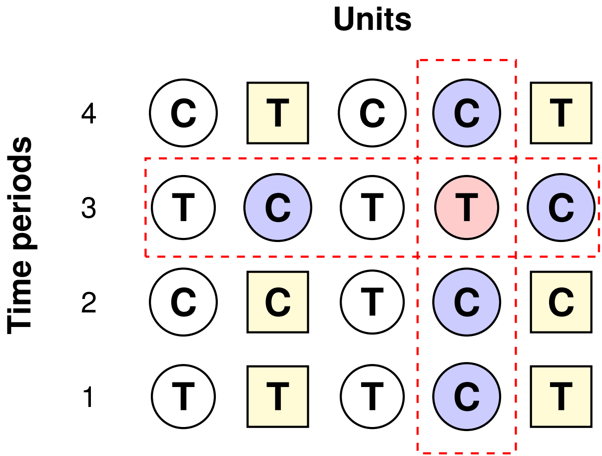
Matching and Two-way Fixed Effects Estimators

- Problem: No other unit shares the same unit and time



- Two kinds of mismatches
  1. Same treatment status
  2. Neither same unit nor same time

We Can Never Eliminate Mismatches

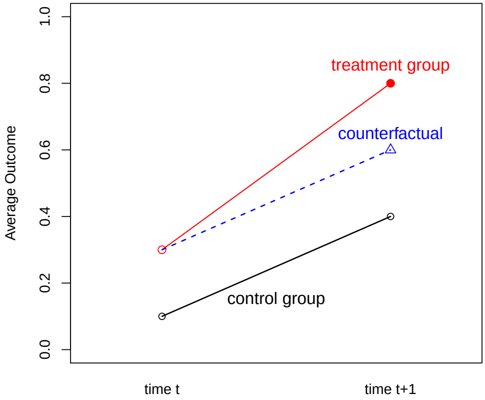


- To cancel time and unit effects, we must induce mismatches
- No weighted two-way fixed effects model eliminates mismatches

Difference-in-Differences Design

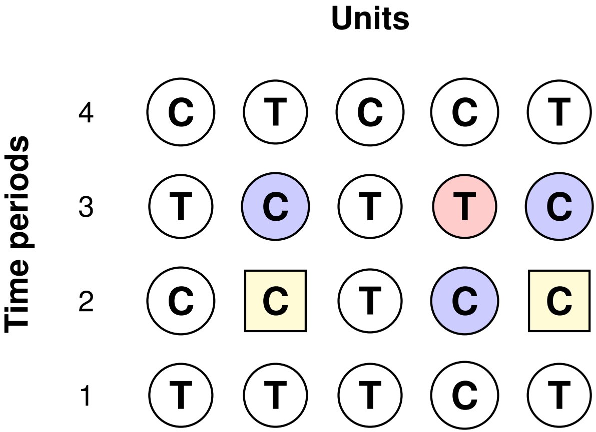
- Replace the model-based assumption with the design-based one
- Parallel trend assumption (not about treatment assignment):

$$
\begin{aligned}
& \mathbb{E}(Y_{it}(0) - Y_{i,t-1}(0) \mid X_{it} = 1, X_{i,t-1} = 0) \\
= \; & \mathbb{E}(Y_{it}(0) - Y_{i,t-1}(0) \mid X_{it} = X_{i,t-1} = 0)
\end{aligned}
$$

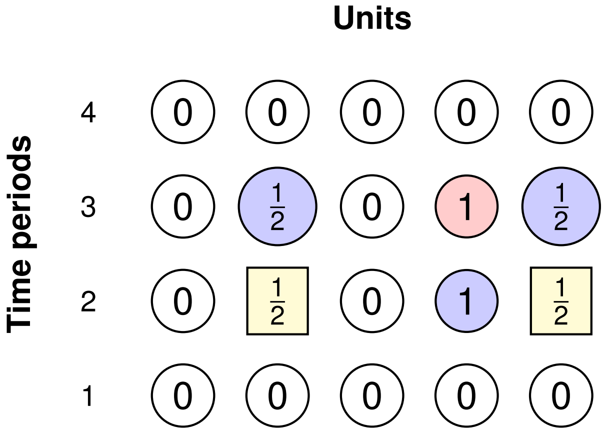


General DiD $=$ Weighted Two-Way FE Effects

- $2 \times 2 \rightsquigarrow$ standard two-way fixed effects estimator works
- General setting: Multiple time periods, repeated treatments



- Regression weights:



- Weights can be negative $\Longrightarrow$ the method of moments estimator
- Fast computation is still available

Effects of GATT Membership on International Trade

1. Controversy
   - Rose (2004): No effect of GATT membership on trade
   - Tomz et al. (2007): Significant effect with non-member participants
2. The central role of fixed effects models:
   - Rose (2004): one-way (year) fixed effects for dyadic data
   - Tomz *et al.* (2007): two-way (year and dyad) fixed effects
   - Rose (2005): "I follow the profession in placing most confidence in the fixed effects estimators; I have no clear ranking between country-specific and country pair-specific effects."
   - Tomz *et al.* (2007): "We, too, prefer FE estimates over OLS on both theoretical and statistical ground"

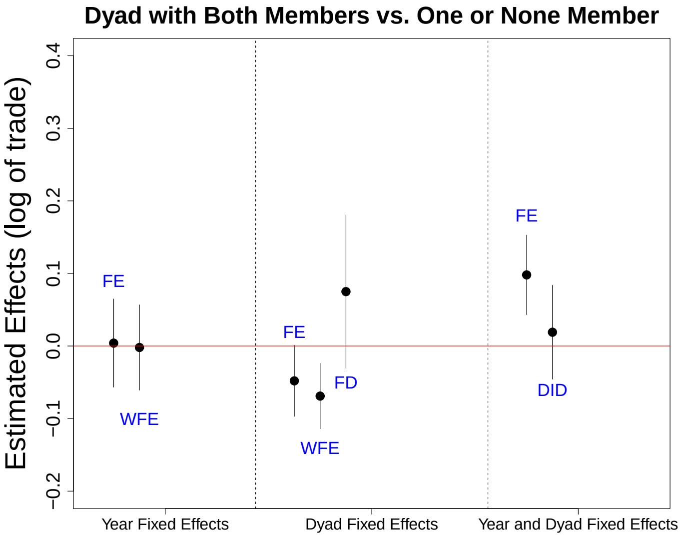
Data and Methods

1. Data
   - Data set from Tomz et al. (2007)
   - Effect of GATT: 1948 – 1994
   - 162 countries, and 196,207 (dyad-year) observations
2. Year fixed effects model:

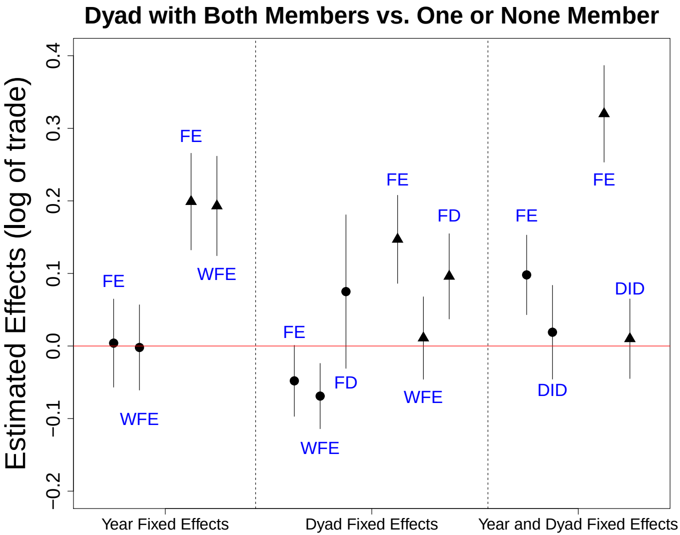
$$\ln Y_{it} \;=\; \alpha_t + \beta X_{it} + \delta^\top \mathbf{Z}_{it} + \epsilon_{it}$$

   - Y_{it}: trade volume
   - X_{it}: membership (formal/participants) Both vs. At most one
   - $\mathbf{Z}_{it}$: 15 dyad-varying covariates (e.g., log product GDP)
3. Assumptions:
   - past membership status doesn't directly affect current trade volume
   - past trade volume doesn't affect current membership status
     $\rightsquigarrow$ not credible
   - Before-and-after: increasing trend in trade volume $\rightsquigarrow$ not credible
   - Difference-in-differences $\rightsquigarrow$ may be most credible

Empirical Results: Formal Membership



Empirical Results



Concluding Remarks

- Linear fixed effects models are attractive because they can adjust for unobserved confounders
- However, this advantage comes at costs
- Two key (under-appreciated) causal assumptions:
  1. past treatments do not directly affect current outcome
  2. past outcomes do not directly affect current treatment
- These assumptions can be relaxed under an alternative selection-on-observables approaches
- A new matching estimator:
  1. Within-unit matching estimator $\rightsquigarrow$ no linearity assumption
  2. Assumptions about time trends: $\rightsquigarrow$ before-and-after and differnece-in-differences
  3. All proposed estimators can be written as weighted linear fixed effects regression estimators
- R package **wfe** is available at CRAN

Send comments and suggestions to:

kimai@Princeton.Edu

More information about this and other research:

http://imai.princeton.edu