

# Causal Inference with Panel Data

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## Potential outcomes framework [5,15]

Suppose I have COVID-19. Would going to the hospital improve my health?

Defining *causal effect* of “go hospital”(D) on my “health”(Y):

- 2 **potential outcomes**:  $Y_i(D = \text{“go”})$  or  $Y_i(D = \text{“stay”})$
- Individual causal effect *defined* by the difference in potential outcomes:

$$Y_i(D = \text{“go”}) - Y_i(D = \text{“stay”})$$

Fundamental problem [13]:

- We **only observe one** of the two potential outcomes  
→ can’t “go” or “stay” at the same time. The other remains as counterfactual
- Cannot infer individual causal effects

Instead, we aim to recover the **average treatment effect** with multiple units

# Average Treatment Effect [15]

Assume that:

1. Treatment assigned independently from outcome and pre-treatment attributes  
(*ignorability*, or “*unconfoundedness*”; “*exogeneity*”; “*selection on observables*”; “*omitted variables*”)
2. Each unit has some chance to receive a treatment (*overlap*; *common support*)
3. Units receive same version of treatment (Stable Unit Treatment Value Assumption)
4. No *spillover* or *carry-over* effects across units and times
5. Treatment effect is *linear*

Under above assumptions, aim to recover following *causal estimands*:

- Average Treatment Effect:

$$E[Y_i(\text{go}) - Y_i(\text{stay})]$$

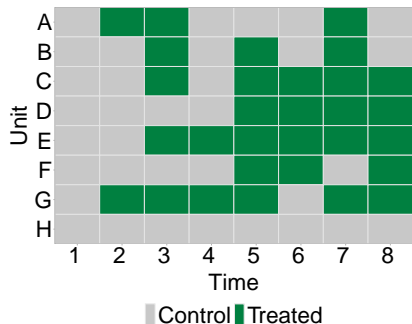
- Average Treatment Effect on the Treated:

$$E[Y_i(\text{go}) - Y_i(\text{stay}) \mid \underbrace{D_i = \text{“go”}}_{\text{treated group}}]$$

## Observational “panel” or “TSCS” data [7]

- Panel: repeated cross-section data (different units sampled over time)
- Time-series-cross-section: “same” units *repeatedly* observed across time periods  
→ Balanced panel
- Today’s methods generally apply to both cases

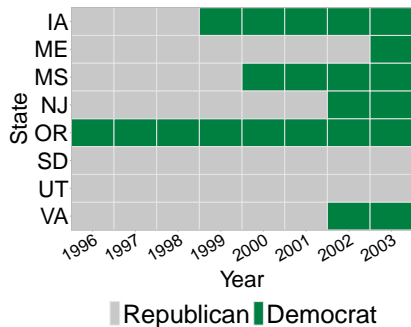
# Mapping panel data onto grids



- Y-axis indicates unit (N)
- X-axis indicates time (T)
- Green cells are treated units
- Grey cells are control units

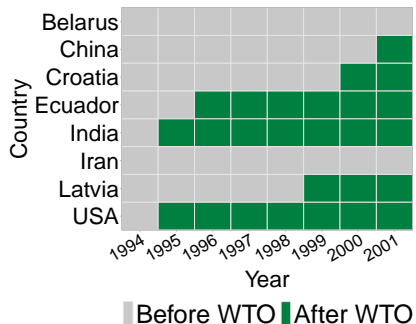
- Treatment is binary (either get treated or remain as control)
- Aim to recover **average treatment effect** or **average treatment effect for the treated** under various settings

# Examples



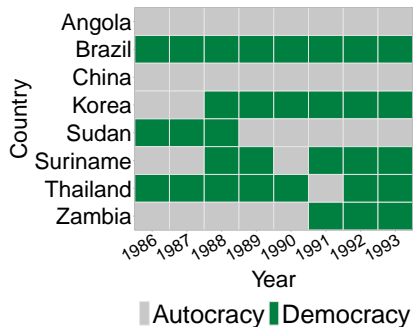
- Does a state governor's party ID affect policy performances?  
(Dynes & Holbein 2019) [[11](#)]

# Examples



- Does WTO accession increase trade?  
(Rose 2004; Tomz, Goldstein & Rivers 2007)  
[18,20]

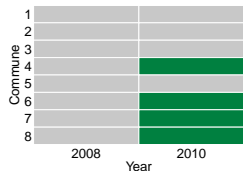
# Examples



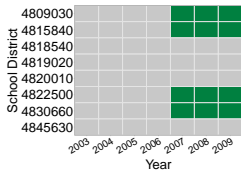
- Does a country's regime type matter for economic growth?  
(Acemoğlu et al. 2019) [1]



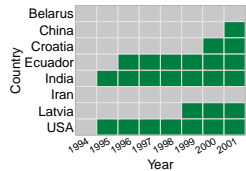
# Panel/TSCS data with heterogeneous treatment paths



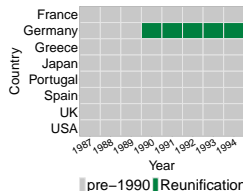
(a) Simple DiD [17]



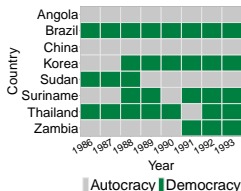
(b) Multi-period DiD [6]



(c) Staggered Adoption

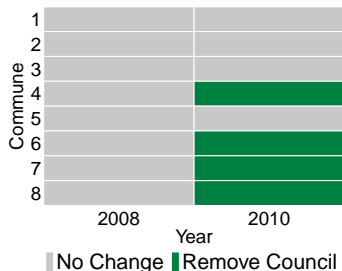


(d) Synthetic Control [3,4]



(e) Treatment Reversal [1]

# Difference-in-Differences design



Malesky et al. (2014, *APSR* [17])

- Question: Does decentralization lead to better public service delivery?
- Treatment: **Removal of elected councils** in Vietnamese districts
- 30 outcome variables (public transport, TV broadcasting, post office, health care...)
- Two periods (2008, 2010), treatment assigned on April 25, 2009
- Two groups (communes that removed vs. maintained councils)

# Identification under a DiD design

## Assumptions:

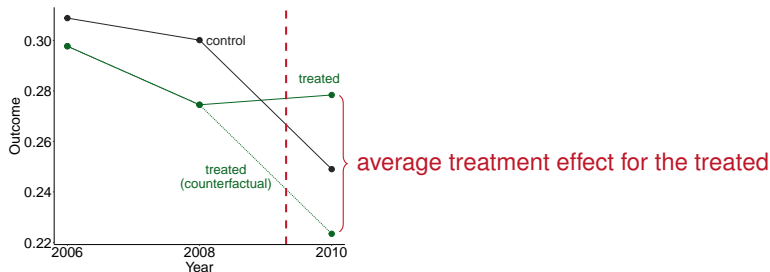
- Treatment is exogenous  $\rightsquigarrow$  not random (treatment carefully assigned)
- Same treatment for each unit  $\rightsquigarrow$  “Removal of councils”
- No spill-over or carry-over effect
- **Linear** treatment effect

Additionally, we assume the **parallel trends** assumption

# “Parallel Trends” assumption

Assume that:

- Pre-treatment trends of the DV is same for treated & control groups



$$\mathbb{E}\left[\underbrace{Y_{i1}(0)}_{\text{post-treat DV}} - \underbrace{Y_{i0}(0)}_{\text{pre-treat DV}} \mid \underbrace{D_i = 1}_{\text{treated}}\right] = \mathbb{E}\left[\underbrace{Y_{i1}(0)}_{\text{post-treat DV}} - \underbrace{Y_{i0}(0)}_{\text{pre-treat DV}} \mid \underbrace{D_i = 0}_{\text{control}}\right]$$

# Estimation

The DiD estimator:

$$\begin{aligned} & (E[\text{treated units' post-treat outcomes}] - E[\text{treated units' pre-treat outcomes}]) \\ & - (E[\text{control units' post-treat outcomes}] - E[\text{control units' pre-treat outcomes}]) \end{aligned}$$

Under the parallel trends assumption, we compute this DiD estimator via:

$$Y_{it} \sim \alpha + \theta D_i + \gamma T_t + \beta(D_i \times T_t)$$

In R, equivalent to:

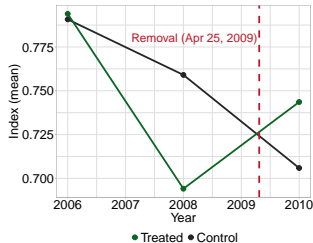
```
lm(y ~ treat + post + treat*post, data = data)
```

- treat ( $D_i$ )  $\in \{0,1\}$  (treatment or control group)
- post ( $T_t$ )  $\in \{0,1\}$  (pre- or post- treatment period)
- control variables can be added

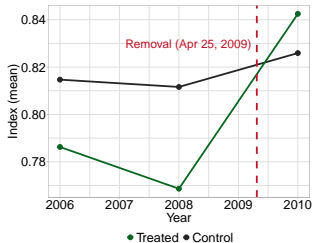
Coefficient for the **treat\*post** ( $\beta$ ) numerically equivalent to the DiD estimator (**ATT**)

# Check the parallel trends assumption

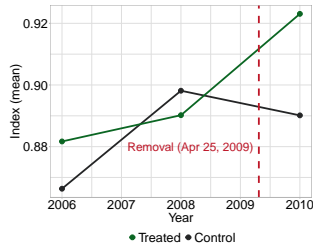
- Plot DV trends for both treated/control group:



(a) Public Transport



(b) TV Broadcasting



(c) Post Office

- What to do when the parallel trends seem implausible?  
⇒ Use information from multiple “pre-treatment” period (ongoing works) [21]

# Summary

## Difference-in-Differences:

- Special case of panel/TSCS data settings
- Importance of the **parallel trends** assumption
- Estimation is straightforward when all assumptions are plausible
- **Linear** treatment effect

## Statistical software on Difference-in-Differences design

- In R:
  - `panelView` (by Xu)
  - `did` (by Callaway & Sant'Anna)
  - `DIDdesign` (by Egami & Yamauchi)
- In STATA:
  - `DID_MULTIPLEGT` (by de Chaisemartin & D'Haultfœuille)
- **caution!** all under development (read documentation carefully)

## Two-way Fixed Effects: Setup [14]

From two units and two time periods to

- multiple units
- multiple periods
- varying treatment adoptions (staggered adoption; treatment status on and off)

### Two-way Fixed Effects (2FE) Model

- Two problems
  - treatment effects heterogeneity
  - unobserved time-varying confounders
- Practical solutions



## Two-way Fixed Effects: Setup [14]

$$Y_{it} = \alpha_i + \gamma_t + \beta(D_i \times T_t) + \epsilon_{it}$$

- $\alpha_i$  is time-invariant unit specific fixed effects (e.g. culture)
- $\gamma_t$  is unit-invariant time specific fixed effects (e.g. pandemic)
- $D_i = 1$  if the unit is ever treated
- $T_t = 1$  if it is the post-treatment time periods
- $\beta$  is the estimate of interests
- Covariates can be easily added

## Two-way Fixed Effects: Setup [14]

2FE model and DID

- **2FE is not equivalent to DID with multiple units and time periods**
- 2FE is equivalent to DID only with two units and two time periods
- The connection between 2FE and DID will be illustrated with an example later

## Two-way Fixed Effects: Setup [9]

Interpret 2FE using potential outcome framework

- Demean: compare  $Y_{it}$  with the average of other observations from the same group
- Estimated counterfactuals in 2FE model:  $M_i + M_t - M_o$
- $M_i$ : mean of other observations from the same group
- $M_t$ : mean of other observations from the same time period
- $M_o$ : mean of other observations from neither the same group nor the same time period
- **There is no observation that is both in the same group and the same time period**

## Two-way Fixed Effects: Setup [9]

### Causal assumptions

1. No unobserved time-varying confounders (parallel trend)
2. Past outcomes do not affect current treatment status (exogeneity)
3. **Linearity assumption (functional form)**
  - Even when 1 and 2 are satisfied, violation of 3 results in inconsistent estimation of  $\beta$

### Note

- Past outcomes are allowed to affect current outcomes: need to cluster standard errors
- Past treatments are allowed to affect current outcomes: add lags and leads
- The leads are often used to test for parallel trend
- Trade-off between fixed effects and lagged dependent variables: assumption 2

## Two-way Fixed Effects: Problems [9]

**Problem: treatment effects heterogeneity across units or over time**

Consequences

- Inconsistent estimation:  $\beta_{2fe}$  could be negative even when ATE for each unit is positive

Why?

## Two-way Fixed Effects: Problems [9]

**Problem: treatment effects heterogeneity across units or over time**

2FE model:  $Y_{it} = \alpha_i + \gamma_t + \beta D_i \times T_t + \epsilon_{it}$

Decompose  $\beta_{2fe}$

- $\beta_{2fe}$  is a weighted average of treatment effects of each treated unit in each time period
- The weights can be negative

## Two-way Fixed Effects: Problems [9]

**Problem: treatment effects heterogeneity across units or over time**

An example: two units and three time periods with staggered treatment adoption

Data generating process:

```
# Treatment assignments
DT <- list(c(0,0,1),c(0,1,1))
# Unit and time specific treatment effects
beta <- list(c(0,0,1),c(0,1,4))
# time invariant unit specific effects
alpha <- list(1.7,2.6)
# unit invariant time specific effects
gamma <- c(0,0,0)
# Data generating process for unit 1 and unit 2
Y_1 <- alpha[[1]] + gamma + beta[[1]]*DT[[1]]
Y_2 <- alpha[[2]] + gamma + beta[[2]]*DT[[2]]
```

## Two-way Fixed Effects: Problems [9]

### **Problem: treatment effects heterogeneity across units or over time**

An example: two units and three time periods with staggered treatment adoption

```
##           id time DT    Y
## 1  Maryland    1  0  1.7
## 2  Maryland    2  0  1.7
## 3  Maryland    3  1  2.7
## 4 California    1  0  2.6
## 5 California    2  1  3.6
## 6 California    3  1  6.6
```



## Two-way Fixed Effects: Problems [9]

Problem: treatment effects heterogeneity across units or over time

An example: two units and three time periods with staggered treatment adoption

Estimate  $\beta_{fe}$  using two-way fixed effects model

```
# 2FE model
m <- lm(data = d_example, Y ~ DT + as.factor(id) + as.factor(time))
beta_fe <- coef(m)[2]
beta_fe

##      DT
## -0.5
```

Why is  $\beta_{fe}$  negative when  $\beta_{MD,t=3} = 1$ ,  $\beta_{CA,t=2} = 1$ , and  $\beta_{CA,t=3} = 4$  are all positive?

## Two-way Fixed Effects: Problems [9]

### Problem: treatment effects heterogeneity across units or over time

An example: two units and three time periods with staggered treatment adoption

```
# calculate the weights
m_weight <- lm(data=d_example, DT ~ as.factor(id) + as.factor(time))
d_example <- d_example %>% mutate(W = m_weight$residuals)
d_example
```

##		id	time	DT	Y	W
## 1	Maryland	1	0	1.7	0.1666667	
## 2	Maryland	2	0	1.7	-0.3333333	
## 3	Maryland	3	1	2.7	0.1666667	
## 4	California	1	0	2.6	-0.1666667	
## 5	California	2	1	3.6	0.3333333	
## 6	California	3	1	6.6	-0.1666667	

## Two-way Fixed Effects: Problems [9]

**Problem: treatment effects heterogeneity across units or over time**

An example: two units and three time periods with staggered treatment adoption

$$\omega_{MD,t=3} = \frac{1}{6}, \omega_{CA,t=2} = \frac{1}{3}, \omega_{CA,t=3} = -\frac{1}{6}$$

After normalization,  $\omega_{MD,t=3} = \frac{1}{2}, \omega_{CA,t=2} = 1, \omega_{CA,t=3} = -\frac{1}{2}$

$$\beta_{fe} = \frac{1}{2} \times 1 + 1 \times 1 - \frac{1}{2} \times 4 = -0.5$$

Why  $\beta_{fe}$  is negative: **heterogenous treatment effects and negative weights**

## Two-way Fixed Effects: Problems [9]

**Problem: treatment effects heterogeneity across units or over time**

An example: two units and three time periods with staggered treatment adoption

The connection between  $\beta_{fe}$  and DID estimator

##	time	California	Maryland
## 1	1	0	0
## 2	2	1	0
## 3	3	1	1

Two DID estimators:  $\beta_{fe} = \frac{DID_1 + DID_2}{2}$

$$DID_1 = (Y_{MD,t=3} - Y_{MD,t=2}) - (Y_{CA,t=3} - Y_{CA,t=2})$$

$$DID_2 = (Y_{CA,t=2} - Y_{CA,t=1}) - (Y_{MD,t=2} - Y_{MD,t=1})$$

## Two-way Fixed Effects: Problems [9,8,16]

**Problem: treatment effects heterogeneity across units or over time**

An example: two units and three time periods with staggered treatment adoption

The connection between  $\beta_{fe}$  and DID estimator

$$DID_1 = (2.7 - 1.7) - (6.6 - 3.6) = -2$$

$$DID_2 = (3.6 - 2.6) - (1.7 - 1.7) = 1$$

$$\beta_{fe} = \frac{-2 + 1}{2} = -0.5$$

Why  $DID_1$  is negative: **treated observations (CA in time 2 and 3) are used as controls**

## Two-way Fixed Effects: Problems [9,8,16]

**Problem: treatment effects heterogeneity across units or over time**

### Summary

- 2FE estimator is a weighted average of treatment effects of each treated unit in each time period
- The weights can be negative
- $\beta_{fe}$  cannot be consistently estimated if treatment effects are heterogenous
- Units adopting the treatment earlier are more likely to receive some negative weights

## Two-way Fixed Effects: Problems [9,8,16]

**Problem: treatment effects heterogeneity across units or over time**

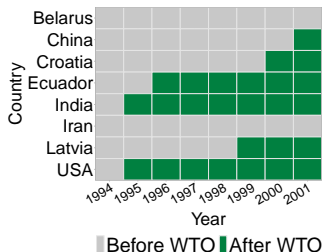
Solutions

- First, compare the treated only with untreated observations (e.g. define  $DID_1 = 0$ )
- Second, calculate unit and time specific treatment effects
- Third, aggregate individual effects in a way without negative weights

# Two-way Fixed Effects: Problems [9,8,16]

**Problem: treatment effects heterogeneity across units or over time**

Solutions: matching based approach



Estimate  $\beta_{Croatia,2000}$

- Find control units from Belarus, China, and Iran
- Estimate  $DID_{2000,pre2000}$

Estimate  $\beta_{Croatia,2001}$

- Find control units from Belarus, Iran
- Estimate  $DID_{2001,pre2000}$

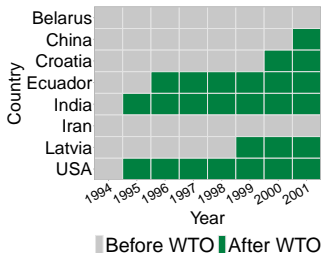
Aggregate  $DID_{2000,pre2000}$  and  $DID_{2001,pre2000}$



# Two-way Fixed Effects: Problems [5,16,19]

**Problem: treatment effects heterogeneity across units or over time**

Solutions: model based approach (R package: *fect*)



- Use all untreated observations (the gray ones), and fit the following 2FE model

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

- Use the estimated  $\hat{\alpha}$  and  $\hat{\gamma}$  to impute counterfactuals for treated observations (the green ones):  $Y(\hat{0})_{it} = \hat{\alpha}_i + \hat{\gamma}_t$
- Calculate treatment effects for unit  $i$  at time period  $t$ :  
 $\beta_{it} = Y_{it}^{observed} - Y(\hat{0})_{it}$
- Aggregate  $\beta_{it}$

## Two-way Fixed Effects: Problems [5,16,19]

**Problem: treatment effects heterogeneity across units or over time**

Solutions: summary

- Only use untreated observations as control units
- Calculate unit and time specific treatment effects, and then aggregate
- Flexibility in choosing control units
- Flexibility in estimating counterfactuals
- Flexibility in aggregating results

## Two-way Fixed Effects: Problems [2,3,4,10]

**Problem: unobserved time-varying confounders (violation of parallel trend)**

Solutions

- Test for (no) pre-trend, allowing heterogeneous effects (otherwise it is problematic)
- Directly model unobserved time-varying confounders
- Both need long pre-treatment periods

## Two-way Fixed Effects: Problems [2,3,4,10]

**Problem: unobserved time-varying confounders (violation of parallel trend)**

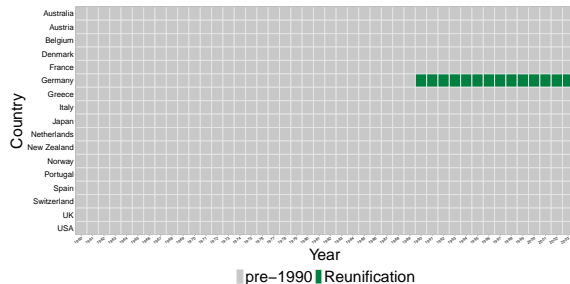
Solutions: test for (no) pre-trend, allowing heterogeneous effects

- The trend between treated and control units before the adoption of treatment
- If parallel pre-treatment, more likely to be parallel post-treatment
- $\beta_{it} = Y_{it}^{observed} - \hat{Y}_{it}(0)$
- Plot  $\beta_{it}$  from  $t = -m, -m + 1, \dots, -2, -1, 0, 1, 2, \dots, m - 1, m$
- Whether the effects in the pre-treatment periods exhibit upward or downward trend
- Visualize
- Formally test:
  - jointly zero
  - equivalent test (flip the null hypothesis)
  - placebo test (move treatment adoption backward)

# Two-way Fixed Effects: Problems [2,3,4,10]

**Problem: unobserved time-varying confounders (violation of parallel trend)**

Solutions: model unobserved time-varying confounders (synthetic control)



- $Y_{Germany} = 0.2Y_{Italy} + 0.3Y_{France} + 0.5Y_{Austria}$
- No control alone follows a parallel trend with Germany
- But a weighted combination of Italy, France, and Austria can be seen as counterfactual outcomes to Germany
- Require a relatively long pre-treatment period

## Two-way Fixed Effects: Problems

**Problem: unobserved time-varying confounders (violation of parallel trend)**

Solutions: model unobserved time-varying confounders (synthetic control)

$$Y_{Germany} = 0.2Y_{Italy} + 0.3Y_{France} + 0.5Y_{Austria}$$

How to understand the weights

- The outcome trajectories of some countries are more similar than others to Germany
  - DID: equal weights are assigned to each control unit
  - countries with very different trends are assigned 0 as weight
- Germany is correlated with other countries in some way
  - estimate the correlations using pre-treatment observations
  - assume that the correlations hold in post-treatment periods
  - use estimated correlations to impute counterfactuals for Germany at each post-treatment period

R package: *Synth*

## Two-way Fixed Effects: Problems

**Problem: unobserved time-varying confounders (violation of parallel trend)**

Solutions: model unobserved time-varying confounders (synthetic control)

With multiple treated units

- Repeat the estimation for each treated unit and aggregate the effects
- Use R package *fect* with interactive fixed effects model (a factor model)

Note

- Parallel trend is not guaranteed, unless it mimics the true data generating process
- But this is easy to check (pre-trend)

# Two-way Fixed Effects: Summary

## Two problems

- Treatment effects heterogeneity
- unobserved time-varying confounders (violation of parallel trend)

## Solutions

## Other notes

- Number of N and T
- Statistical inference (standard errors): randomized inference or bootstrap



## *fect*: Fixed Effects Counterfactual Estimators

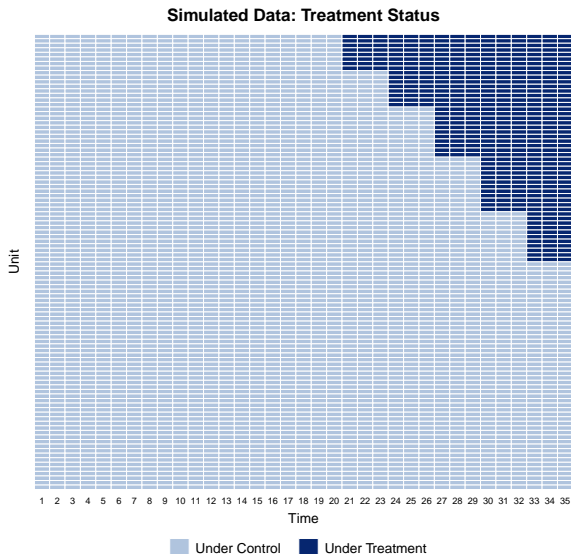
Installation and user instruction: <http://yiqingxu.org/software/fect/fect.html>

Reference: Licheng Liu, Ye Wang, Yiqing Xu (2019). "A Practical Guide to Counterfactual Estimators for Causal Inference with Time-Series Cross-Sectional Data." Available at SSRN: <https://papers.ssrn.com/abstract=3555463>.

## fect: Fixed Effects Counterfactual Estimators

```
# load required packages
library(fect)
library(panelView)
# load the data
data(fect)
# view the data
panelView(Y ~ D, data = simdata1, index = c("id", "time"),
          by.timing = TRUE,
          axis.lab = "time", xlab = "Time", ylab = "Unit",
          show.id = c(1:100),
          background = "white",
          main = "Simulated Data: Treatment Status")
```

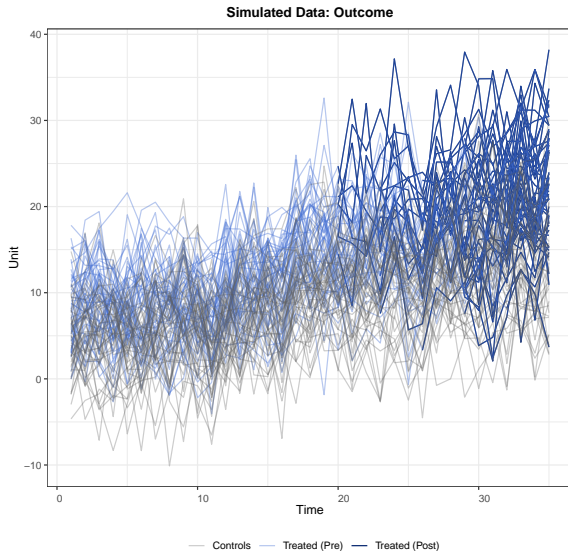
# *fect*: Fixed Effects Counterfactual Estimators



## *fect*: Fixed Effects Counterfactual Estimators

```
# view the outcome  
panelView(Y ~ D, data = simdata1, index = c("id", "time"),  
  axis.lab = "time", xlab = "Time", ylab = "Unit", show.id = c(1:100),  
  theme.bw = TRUE, type = "outcome", main = "Simulated Data: Outcome")
```

# *fect*: Fixed Effects Counterfactual Estimators



# fect: Fixed Effects Counterfactual Estimators

```
# 2FE counterfactual estimator  
out.fect <- fect(Y ~ D + X1 + X2,  
                data = simdata1, index = c("id", "time"),  
                force = "two-way", se = TRUE, nboots = 200)
```

```
# ATE: equally weight each observation
```

```
out.fect$est.avg
```

```
##          ATT.avg          S.E. CI.lower CI.upper p.value  
## [1,] 3.489078 0.402998 2.699216 4.278939          0
```

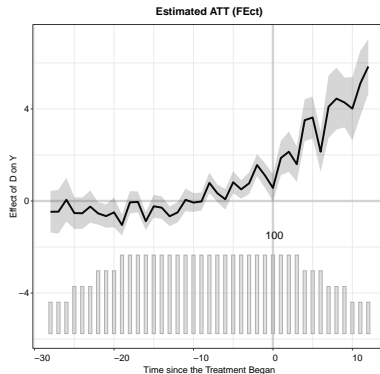
```
# ATE: equally weight each unit
```

```
out.fect$est.avg.unit
```

```
##          ATT.avg.unit          S.E. CI.lower CI.upper          p.value  
## [1,]          2.928551 0.3673738 2.208512 3.64859 1.554312e-15
```

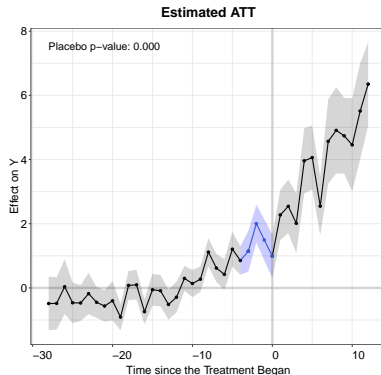
# fect: Fixed Effects Counterfactual Estimators

```
# plot the estimated ATT  
plot(out.fect, main = "Estimated ATT (FEct)", ylab = "Effect of D on Y",  
      cex.main = 0.8, cex.lab = 0.8, cex.axis = 0.8)
```



# fect: Fixed Effects Counterfactual Estimators

```
# a placebo test
out.fect.p <- fect(Y ~ D + X1 + X2, data = simdata1,
  index = c("id", "time"), force = "two-way", se = TRUE, nboots = 200,
  placeboTest = TRUE, placebo.period = c(-3, 0))
plot(out.fect.p, cex.text = 0.8)
```





# *fect*: Fixed Effects Counterfactual Estimators

Not parallel, what can we do

- Interactive fixed effects model
  - A factor model
  - Helpful only when the data follows a factor structure
  - Need a cross validation process to choose the number of factors

```
out.ife <- fect(Y ~ D + X1 + X2, data = simdata1, index = c("id", "time"),  
               force = "two-way", method = "ife",  
               CV = TRUE, r = c(0, 5),  
               se = TRUE, nboots = 200,)
```

- Match each treated unit with similar control units from the never treated

# Thank you!

Slides and other materials available from:

<https://github.com/EandrewJones/gvpt-methods>

Follow-up Questions:

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