Difference-in-Differences in Stata 17

StataCorp LLC

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Difference-in-differences (DID)

- One of the most popular causal effects estimators (1855)
- Understand the effect of a treatment on an outcome for the treated group
  - Subsidy on productivity
  - A drug on cholesterol levels
  - An after-school program on GPA

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  - Observational data for repeated cross-sectional and panel data

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    - Identification does not depend on controlling for covariates
    - Identification hinges on control for group and time unobservable characteristics

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- How is it different from other treatment effects estimators?
  - Observational data for repeated cross-sectional and panel data
  - Identification does not depend on controlling for covariates
  - Identification hinges on control for group and time unobservable characteristics
- Estimate of causal effect of a treatment controlling for unobservables

Stata implementation

- Two-way fixed effects also known as generalized DID (default)
- Allows 2x2 design
- Provides a wide range of standard errors
- Provides diagnostics and tests
- Binary or continuous treatment
- Difference-in-difference-in-differences (DDD) with group and time interactions

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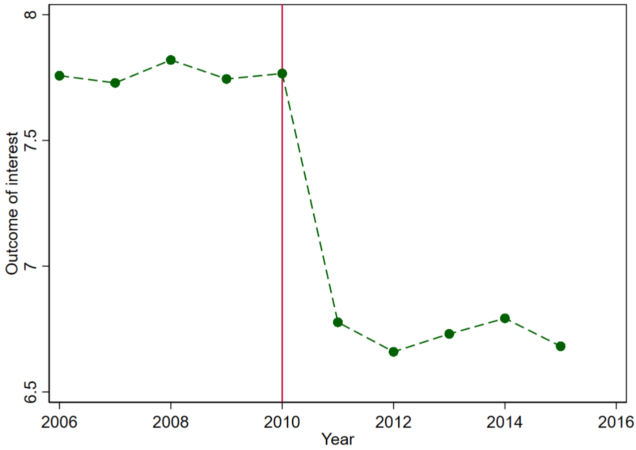
- Two-way fixed effects also known as generalized DID (default)
- Allows 2x2 design
- Provides a wide range of standard errors
- Provides diagnostics and tests
- Binary or continuous treatment
- Difference-in-difference-in-differences (DDD) with group and time interactions
- Caveats
  - Treatment effects are homogeneous
  - Standard error literature is large and growing
  - Diagnostics and tests

Outline

- Basic concepts
- Stata examples

Basic Concepts

Treated group



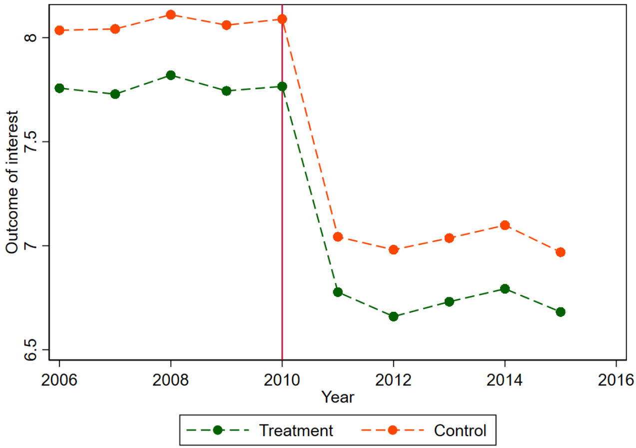
What have we learned

- Clearly there is a change in the outcome after treatment for the treated
- Is it causal?
    - Time specific effects. Another policy. Covid-19.
    - Group unobservable characteristics correlated to treatment. Jargon.

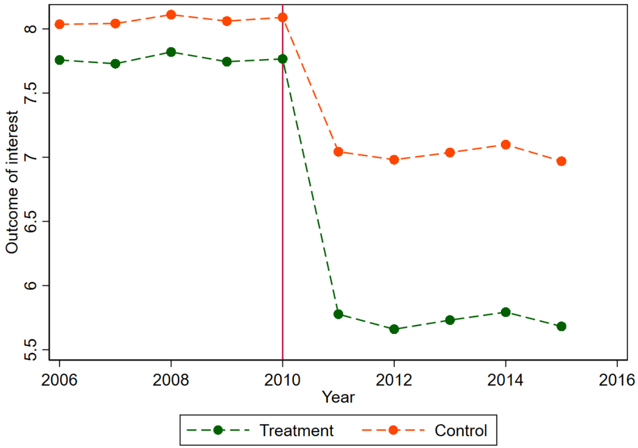
What have we learned

- Clearly there is a change in the outcome after treatment for the treated
- Is it causal?
    - Time specific effects. Another policy. Covid-19.
    - Group unobservable characteristics correlated to treatment. Jargon.
- What can we do?
    - Control for time-specific effects
    - Control for group-specific unobservables (fixed-effects)
    - Use a causal-inference framework

Graphical representation I



Graphical representation II



Card and Krueger (1994)

- Intervention: Increase in the minimum wage
- Group: New Jersey and Pennsylvania
- Outcome: Employment

Linear Framework: Card and Krueger (1994)

- Individuals (i) in a state (s) at two time period $t \in \{0, 1\}$
- Potential outcomes (for now no covariates):

$$\begin{aligned} E\left(y_{ist0} | s, t\right) &= \lambda_t + \gamma_s \\ E\left(y_{ist1} | s, t\right) &= \lambda_t + \gamma_s + \beta \end{aligned}$$

- λ_t is a time effect
- γ_s is a state effect

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- Potential outcomes (for now no covariates):

$$
\begin{aligned}
E\left(y_{ist0}|s,t\right) &= \lambda_t + \gamma_s \\
E\left(y_{ist1}|s,t\right) &= \lambda_t + \gamma_s + \beta
\end{aligned}
$$

- λ_t is a time effect
- γ_s is a state effect
- y_{ist1} is only observed if state s at time t receives the treatment, an increase in minimum wage, $D_{st} = 1$
- y_{ist0} is only observed if state s at time t does not receive the treatment, $D_{st} = 0$

Card and Krueger (1994) continued

- New Jersey increased minimum wage in April (treatment)
- Neighboring Pennsylvania did not (control)
- Before wage change in February:

$$
\begin{aligned}
E\left(y_{ist} | PA, Feb\right) &= \lambda_{Feb} + \gamma_{PA} \\
E\left(y_{ist} | NJ, Feb\right) &= \lambda_{Feb} + \gamma_{NJ} \\
E\left(y_{ist} | NJ, Feb\right) - E\left(y_{ist} | PA, Feb\right) &= \gamma_{NJ} - \gamma_{PA}
\end{aligned}
$$

Card and Krueger (1994) continued

- New Jersey increased minimum wage in April (treatment)
- Neighboring Pennsylvania did not (control)
- Before wage change in February:

$$
\begin{aligned}
E\left(y_{ist}|PA, Feb\right) &= \lambda_{Feb} + \gamma_{PA} \\
E\left(y_{ist}|NJ, Feb\right) &= \lambda_{Feb} + \gamma_{NJ} \\
E\left(y_{ist}|NJ, Feb\right) - E\left(y_{ist}|PA, Feb\right) &= \gamma_{NJ} - \gamma_{PA}
\end{aligned}
$$

- The model assumes a common time trend and differing state effects
- Differencing eliminates unobserved time effects

Card and Krueger (1994) continued

- After the minimum wage change, in November:

$$E\left(y_{ist}|NJ, Nov\right) - E\left(y_{ist}|PA, Nov\right) = \gamma_{NJ} - \gamma_{PA} + \beta$$

- Difference-in-differences looks at differences before and after the policy:

$$\left[E\left(y_{ist}|., Nov\right) - E\left(y_{ist}|., Nov\right)\right] - \left[E\left(y_{ist}|., Feb\right) - E\left(y_{ist}|., Feb\right)\right]$$

Card and Krueger (1994) continued

- After the minimum wage change, in November:

$$E\left(y_{ist}|NJ, Nov\right) - E\left(y_{ist}|PA, Nov\right) = \gamma_{NJ} - \gamma_{PA} + \beta$$

- Difference-in-differences looks at differences before and after the policy:

$$\left[E\left(y_{ist}|., Nov\right) - E\left(y_{ist}|., Nov\right)\right] - \left[E\left(y_{ist}|., Feb\right) - E\left(y_{ist}|., Feb\right)\right]$$

- The difference in these two differences is β
- It is also the average treatment effect on the treated (ATT)

Parallel trends

- y_{ist0} potential outcome of not being treated
- $D_{st} \equiv D$ if group s was treated at time t, $D \in \{0, 1\}$
- s and t are $\in \{0, 1\}$
- At $t = 0$ no one is treated
- Parallel trends:

$$\underbrace{E\left(y_{ist0} | s = 1, D = 1, t = 1\right)}_{\text{potential outcome of treated in group } s = 1 \text{ had they remained untreated at } t = 1}$$

Parallel trends

- y_{ist0} potential outcome of not being treated
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$$\underbrace{E\left(y_{ist0}|s=1, D=1, t=1\right)}_{\text{potential outcome of treated in group } s=1 \text{ had they remained untreated at } t=1}$$

$$E\left(y_{ist0}|s=1, D=1, t=1\right) - E\left(y_{ist0}|s=1, D=1, t=0\right) =$$
$$E\left(y_{ist0}|s=0, D=1, t=1\right) - E\left(y_{ist0}|s=0, D=1, t=0\right)$$

- Could be conditional on covariates

Observed Outcome and Estimating equation

$$
\begin{aligned}
E\left(y_{ist}|s,t\right) &= D_{st}E\left(y_{ist1}|s,t\right)+\left(1-D_{st}\right)E\left(y_{ist0}|s,t\right)\\
E\left(y_{ist}|s,t\right) &= D_{st}\left(\lambda_t+\gamma_s+\beta\right)+\left(1-D_{st}\right)\left(\lambda_t+\gamma_s\right)\\
E\left(y_{ist}|s,t\right) &= \lambda_t+\gamma_s+D_{st}\beta
\end{aligned}
$$

- This suggests fitting a regression model with a dummy variable D_{st}
- The specification could have regressors

Generalized DID or two-way fixed effects

$$y_{ist} = \gamma_s + \gamma_t + D_{st}\beta + \varepsilon_{ist}$$

- D_{st} is an observation level indicator of treatment $D_{st} \in \{0, 1\}$
- In panel data if individuals are nested in s individual effect absorb state effects
- You may include covariates in the specification above

2 x 2 specification DID

$$y_{its} = \gamma_{\mathbb{1}treated} + \gamma_{\mathbb{1}post} + \mathbb{1}treated \times \mathbb{1}post\beta + \varepsilon_{its}$$

- Works when all units are treated at the same time (balanced)
- This model is nested in the generalized DID
  - $\mathbb{1}treated$ is a linear combination of the group dummies
  - $\mathbb{1}post$ is a linear combination of the time dummies
- This model assumes all post periods and all treatment groups are equivalent.

Alternative specifications

- D_{st} is not binary but continuous (intensity of treatment)
- Differences occur between two groups (differencing two group unobservables)
- DDD or triple differences. It incorporates unobservables from two control groups.
  - Number of parameters is large
  - Identification is more challenging

Standard error computation

Treatment occurs at the group level, state, county, country, etc. and time

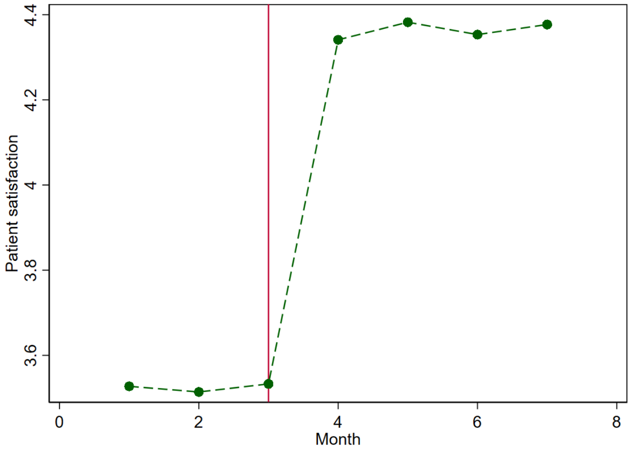
- Cluster at the group level Bertrand, Dufflo, Mullainathan (2004)
- Few number of elements in the group:
  - Donald and Lang (2007) aggregation and other aggregation methods
  - Wild-cluster bootstrap
  - Bias-corrected standard errors with Bell and McCaffrey (2002) degrees of freedom adjustment
  - Other suggestions

Stata Examples

Artificial data

```
 . webuse hospdd, clear
(Artificial hospital admission procedure data)
. describe
Contains data from https://www.stata-press.com/data/r17/hospdd.dta
 Observations:         7,368                 Artificial hospital admission
                                               procedure data
    Variables:             5                 7 Mar 2021 19:52
------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
------------------------------------------------------------------------------
hospital        byte    %9.0g                 Hospital ID
frequency       byte    %9.0g      size       Hospital visit frequency
month           byte    %8.0g      mnth       Month
procedure       byte    %9.0g      pol        Admission procedure
satis           float   %9.0g                 Patient satisfaction score
------------------------------------------------------------------------------
Sorted by: hospital
```

Graphical representation III



Estimation

```
. didregress (satis) (procedure), group(hospital) time(month)
Number of groups and treatment time
Time variable: month
Control:        procedure = 0
Treatment:      procedure = 1
```

	Control	Treatment
Group		
hospital	28	18
Time		
Minimum	1	4
Maximum	1	4

```
Difference-in-differences regression                    Number of obs = 7,368
Data type: Repeated cross-sectional
                              (Std. err. adjusted for 46 clusters in hospital)
```

satis	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ATET						
procedure (New vs Old)	.8479879	.0321121	26.41	0.000	.7833108	.912665

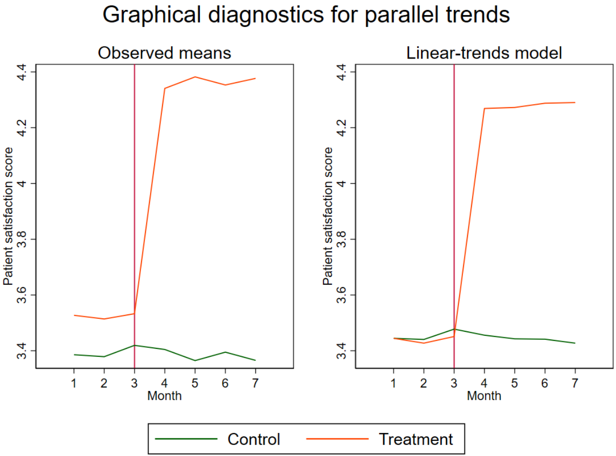
Note: ATET estimate adjusted for group effects and time effects.

Diagnostic plots

```
estat trendplot
```

- First plot: Mean of the outcome for treated and untreated units
- Second plot: Trend of treated and control groups (group interacted with time)

Diagnostic plots



Tests: estat ptrends

```
. estat ptrends
Parallel-trends test (pretreatment time period)
H0: Linear trends are parallel
F(1, 45) =   0.55
Prob > F = 0.4615
```

- Augmented model with trends for treated vs. control group before and after treatment. Test if the pretreatment trends are parallel.

Tests: estat granger

```
. estat granger
Granger causality test
H0: No effect in anticipation of treatment
F(2, 45) =   0.33
Prob > F = 0.7239
```

- Augment the model to include dummies as if treatment had occurred in the past. Test coefficients jointly.

A 2×2 specification

- Create dummy variables for treated group and post time period
- Tell `didregress` not to include group and time effects
- Add dummies to the outcome equation

A 2×2 specification

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- Tell `didregress` not to include group and time effects
- Add dummies to the outcome equation

```
. bysort hospital: egen treated = mean(procedure)
. replace treated = 1 if treated>0
(3,064 real changes made)
. generate post = 0
. replace post = 1 if month>3
(3,684 real changes made)
```

A 2×2 specification

```
. didregress (satis treated post) (procedure),    ///
>          group(hospital) time(month) nogteffects
Number of groups and treatment time
Time variable: month
Control:        procedure = 0
Treatment:      procedure = 1
-----------------------------------
             |   Control  Treatment
-------------+---------------------
Group        |
    hospital |        28         18
-------------+---------------------
Time         |
     Minimum |         1          4
     Maximum |         1          4
-----------------------------------

Difference-in-differences regression                    Number of obs = 7,368
Data type: Repeated cross-sectional
                              (Std. err. adjusted for 46 clusters in hospital)
------------------------------------------------------------------------------
             |               Robust
       satis | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
ATET         |
   procedure |
        (New |
          vs |
         Old)|   .8479879   .0320051    26.50   0.000     .7835263    .9124494
------------------------------------------------------------------------------
Note: ATET estimate adjusted for covariates.
```

Difference-in-difference-in-differences DDD

- Augmented DID

Difference-in-difference-in-differences DDD

- Augmented DID
- Selection on unobservables provides identification
- What if there are unobservables that vary at the group and time level
- Find a new group not exposed to treatment but exposed to the problematic time-varying confounder
- Subtract the effect of that group from the original DID

Difference-in-difference-in-differences DDD

- Augmented DID
- Selection on unobservables provides identification
- What if there are unobservables that vary at the group and time level
- Find a new group not exposed to treatment but exposed to the problematic time-varying confounder
- Subtract the effect of that group from the original DID
- In our example think about individual's frequency of visit affecting satisfaction

DDD preparing my data

```
. generate hightrt = procedure==1 & (frequency==3 | frequency==4)
. label define trt 0 "Untreated" 1 "Treated"
. label values hightrt trt
```

DDD estimation

```
. didregress (satis) (hightrt), group(hospital frequency) time(month)
  (output omitted )
Number of groups and treatment time
Time variable: month
Control:       hightrt = 0
Treatment:     hightrt = 1
```

	Control	Treatment
Group		
hospital	28	18
frequency	2	2
Time		
Minimum	1	4
Maximum	1	4

```
Triple-differences regression                          Number of obs = 7,368
Data type: Repeated cross-sectional
                              (Std. err. adjusted for 46 clusters in hospital)
```

satis	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]	
ATET						
hightrt (Treated vs Untreated)	.764154	.0402603	18.98	0.000	.6830655	.8452425

Note: ATET estimate adjusted for group effects, time effects, and group- and time-effects interactions.

Other estimation alternatives

- `didregress (y x1 ...  xk) (c, continuous), ...`
- `didregress (y ...)  (d...), group(g1 g2)`
- `xtdidregress (y x1 ...  xk) (d), group(`*groupvar*`) time(`*timevar*`)`

Standard error considerations

- Default standard errors are cluster robust standard errors at the group level BDM (2004)
- `didregress` is equivalent to `areg` considers group fixed effects as regressors in the degrees of freedom adjustment
- `xtdidregress` is equivalent to `xtreg` does not consider group fixed effects as regressors
- When the number of elements per groups (states, counties, countries) is small cluster robust standard errors do not work well. Alternatives are:
  - Wild cluster bootstrap
  - Bias corrected standard errors
  - Aggregation methods

Wild-cluster bootstrap

- Covariates remain the same across iteration
- We impose the null hypothesis of $ATET = 0$
- What changes is the weights given to residuals at each iteration $\tilde{y} = X\tilde{\beta} + \tilde{\varepsilon}$, $\tilde{\beta}$, and $\tilde{\varepsilon} = \widehat{\varepsilon} * w$
- No standard errors are computed (rely on normal approximation)
- P-values and confidence intervals are computed
- Algorithm computes p-values and then solves a bisection-algorithm to get CI
- Problem to find CI upper bound and CI lower bound are two separate optimization problems

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- No standard errors are computed (rely on normal approximation)
- P-values and confidence intervals are computed
- Algorithm computes p-values and then solves a bisection-algorithm to get CI
- Problem to find CI upper bound and CI lower bound are two separate optimization problems
- Speed is substantially improved for the next update

Error weights

Error weight	Formula
`rademacher`	-1 with pr 0.5 and 1 with pr 0.5
`mammen`	$1-\phi$ with pr $\phi/\sqrt(5)$, ϕ otherwise, $\phi=(1+\sqrt{5})/2$
`webb`	-$\sqrt{3/2}$, -$\sqrt{2/2}$, -$\sqrt{1/2}$, $\sqrt{1/2}$, $\sqrt{2/2}$, $\sqrt{3/2}$ pr 1/6
`normal`	standard normal
`gamma`	shape parameter 4 scale parameter 1/2

Wildbootstrap I

```
. didregress (satis) (procedure), ///
>         group(hospital) time(month) wildbootstrap(rseed(111))
computing 1000 replications
Finding p-value
.................................................. 50%
.................................................. 100%
Confidence interval lower bound
.....
Confidence interval upper bound
............
```

(*output omitted*)

Wildbootstrap II

```
. didregress (satis) (procedure), ///
>           group(hospital) time(month) wildbootstrap(rseed(111))
  (output omitted)
Number of groups and treatment time
Time variable: month
Control:      procedure = 0
Treatment:    procedure = 1
─────────────────────────────────────
             │   Control   Treatment
─────────────┼───────────────────────
Group        │
   hospital  │        28          18
─────────────┼───────────────────────
Time         │
     Minimum │         1           4
     Maximum │         1           4
─────────────────────────────────────

DID with wild-cluster bootstrap inference             Number of obs   = 7,368
                                                      No. of clusters =    46
                                                      Replications    = 1,000

Data type:    Repeated cross-sectional
Error weight: rademacher
───────────────────────────────────────────────────────────────────────────
       satis │ Coefficient       t     P>|t|       [95% conf. interval]
─────────────┼─────────────────────────────────────────────────────────────
ATET         │
   procedure │
 (New vs Old)│   .8479879   26.41   0.000       .7806237     .9157614
───────────────────────────────────────────────────────────────────────────
Note: ATET estimate adjusted for group effects and time effects.
```

Bias-corrected standard errors

- Cluster generalization of HC2 (scale residuals inverse of square of diagonals from projection matrix)
- Bell and McCaffrey (2002) suggest a degrees of freedom adjustment (per parameter)

Bias-corrected SEs

```
. didregress (satis) (procedure), group(hospital) time(month) vce(hc2)
Computing degrees-of-freedom:
procedure .........
Number of groups and treatment time
Time variable: month
Control:       procedure = 0
Treatment:     procedure = 1
-----------------------------------
             |  Control  Treatment
-------------+---------------------
Group        |
    hospital |       28         18
-------------+---------------------
Time         |
     Minimum |        1          4
     Maximum |        1          4
-----------------------------------

Difference-in-differences regression                  Number of obs   = 7,368
                                                      No. of clusters =    46
Data type: Repeated cross-sectional
------------------------------------------------------------------------------
             |             Robust HC2
       satis | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
ATET         |
   procedure |
        (New |
          vs |
        Old) |   .8479879   .0325552    26.05   0.000     .7819941    .9139816
------------------------------------------------------------------------------
Note: ATET estimate adjusted for group effects and time effects.
```

Degrees of freedom adjustment

```
. mat list r(table)
r(table)[9,9]
              ATET:   Controls:   Controls:   Controls:   Controls:   Controls:
            r1vs0.         1b.          2.          3.          4.          5.
         procedure       month       month       month       month       month
     b   .84798786           0  -.00960766   .02196858  -.00328387  -.00940274
    se   .03255515           .   .01836738   .01817606   .02210113   .02325151
     t   26.047731           .  -.52308262   1.2086544  -.14858393  -.40439255
pvalue   3.558e-25           .   .60348306   .23310851   .88254581   .68783978
    ll    .7819941           .  -.04660147  -.01463989  -.04779783  -.05623368
    ul   .91398163           .   .02738615   .05857705   .04123009    .0374282
    df   36.496106          45          45          45          45          45
  crit   2.0271372   2.0141034   2.0141034   2.0141034   2.0141034   2.0141034
 eform           0           0           0           0           0           0
          Controls:   Controls:   Controls:
                6.          7.
             month       month       _cons
     b  -.00383754  -.01119415    3.444675
    se   .01906173    .0230133   .01140018
     t   -.2013216  -.48642083   302.15965
pvalue   .84135438   .62902945   4.517e-76
    ll  -.04222984   -.0575453   3.4217139
    ul   .03455476   .03515701   3.4676362
    df          45          45          45
  crit   2.0141034   2.0141034   2.0141034
 eform           0           0           0
```

Aggregation methods

$$
\begin{aligned}
y_{its} &= \gamma_s + \gamma_t + z_{1ist}\beta_1 + z_{2st}\beta_2 + D_{st}\delta + \varepsilon_{ist} \\
y_{ist} &= z_{1ist}\beta_2 + C_{st} + \varepsilon_{ist} \\
\widehat{C}_{st} &= z_{2st}\beta_2 + D_{st}\delta + \nu_{st}
\end{aligned}
$$

- Obtain $\widehat{C}_{st}$
- Aggregate at the s, t level and regress
  - `dlang, constant`: regress $\widehat{C}_{st}$ on z_{2st}, D_{st} and time and group fixed effects, degrees of freedom are a function of the level of aggregation *st*
  - `standard`: regress $\widehat{C}_{st}$ on z_{2st}, D_{st}
  - `dlang, varying`: $\widehat{C}_{st}$ is the constant of a regression of each group defined by *st*, i.e. β_1 is not constant but varying.

aggregate(dlang)

```
. didregress (satis) (procedure), group(hospital) time(month) aggregate(dlang)
Number of groups and treatment time
Time variable: month
Control:       procedure = 0
Treatment:     procedure = 1
```

	Control	Treatment
Group		
hospital	28	18
Time		
Minimum	1	4
Maximum	1	4

```
Difference-in-differences regression                   Number of obs = 322
Data type:   Repeated cross-sectional
Aggregation: Donald-Lang
```

satis	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
ATET						
procedure (New vs Old)	.8500467	.0255727	33.24	0.000	.7997311	.9003623

Note: ATET estimate adjusted for group effects and time effects.

aggregate(standard)

```
. didregress `specs´, group(hospital) time(month) aggregate(standard) vce(hc2)
Computing degrees-of-freedom:
procedure .........
Number of groups and treatment time
Time variable: month
Control:       procedure = 0
Treatment:     procedure = 1
-----------------------------------
             |   Control  Treatment
-------------+---------------------
Group        |
    hospital |        28         18
-------------+---------------------
Time         |
     Minimum |         1          4
     Maximum |         1          4
-----------------------------------
Difference-in-differences regression                 Number of obs    = 322
                                                     No. of clusters =   46
Data type:    Repeated cross-sectional
Aggregation:  Standard
------------------------------------------------------------------------------
             |               Robust HC2
       satis | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
ATET         |
   procedure |
        (New |
          vs |
        Old) |   .8500467   .0329513    25.80   0.000     .7832444     .916849
------------------------------------------------------------------------------
Note: ATET estimate adjusted for group effects and time effects.
```

Conclusions

- DID and DDD estimation for cross-sectional and panel-data
- Graphical diagnostics and tests to validate identification strategy
- Standard errors for situations with the number of groups is small
- Just a first step from which we will build