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 hinges on control for group and time unobservable characteristics

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  - 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
  - https://friosavila.github.io/playingwithstata/index.html

Outline

- Basic concepts
- Stata examples

Basic Concepts

Treated group
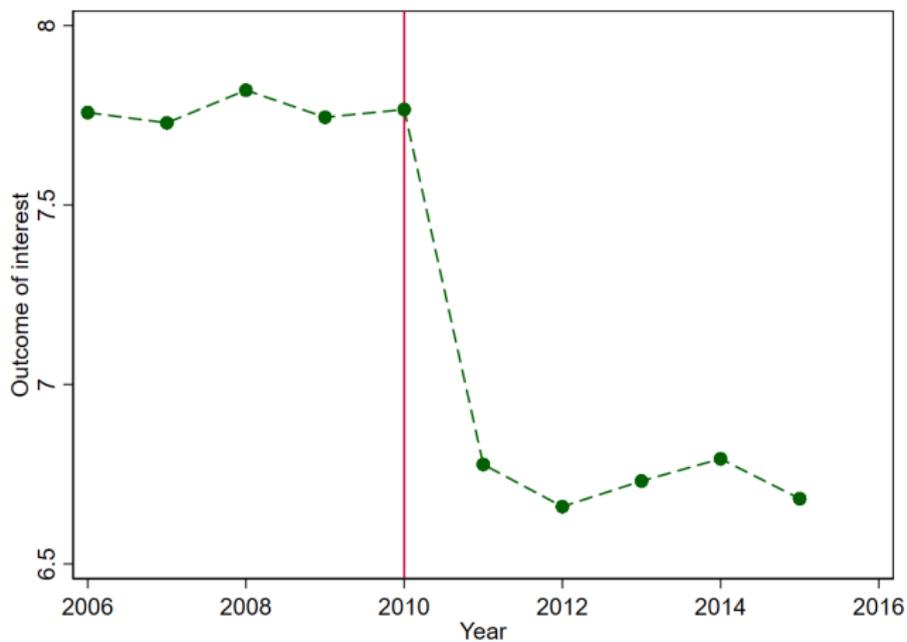
What have we learned

- 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
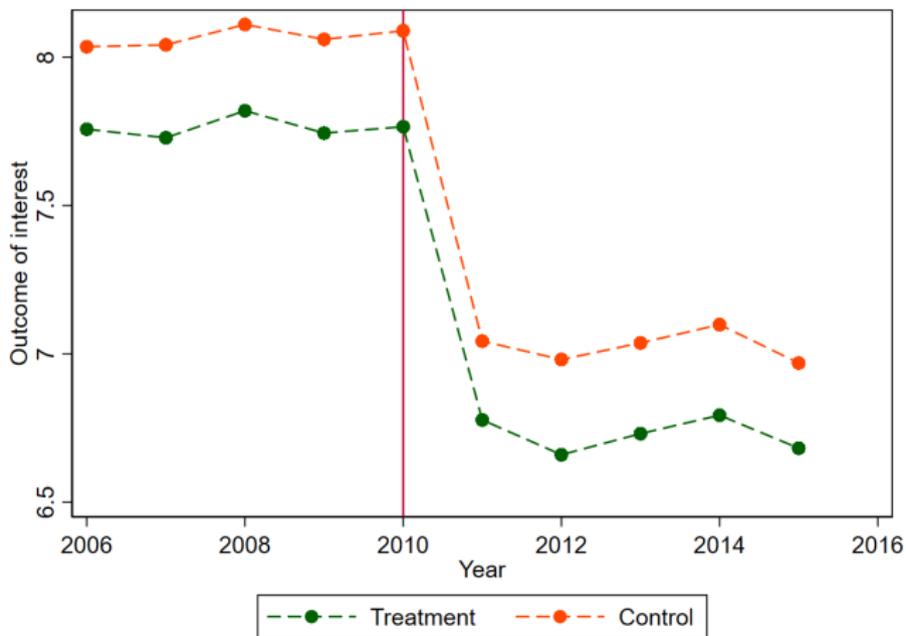
Graphical representation II
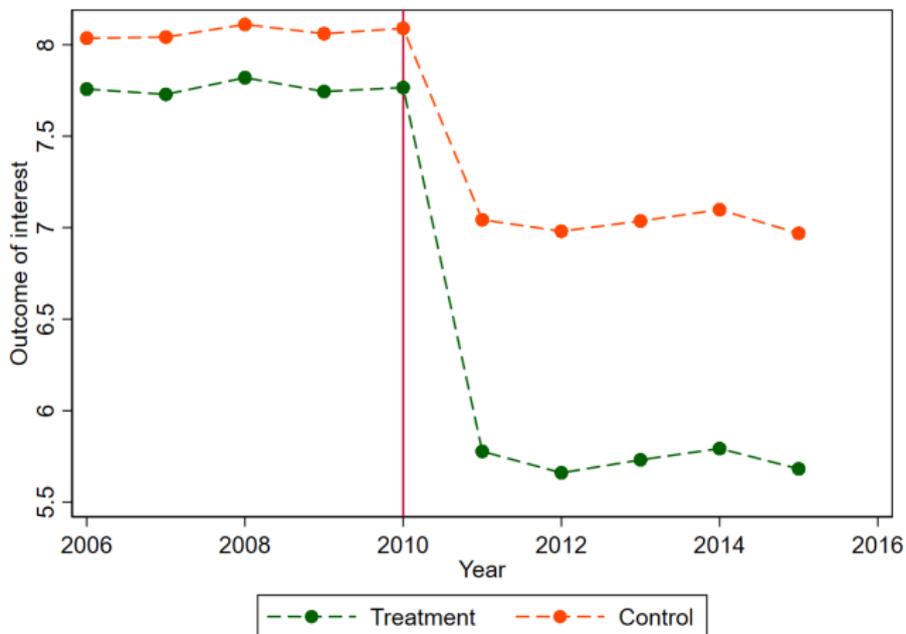
Card and Krueger (1994)

- 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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- 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:

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

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:

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

- 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

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potential outcome of treated in group $s = 1$ 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
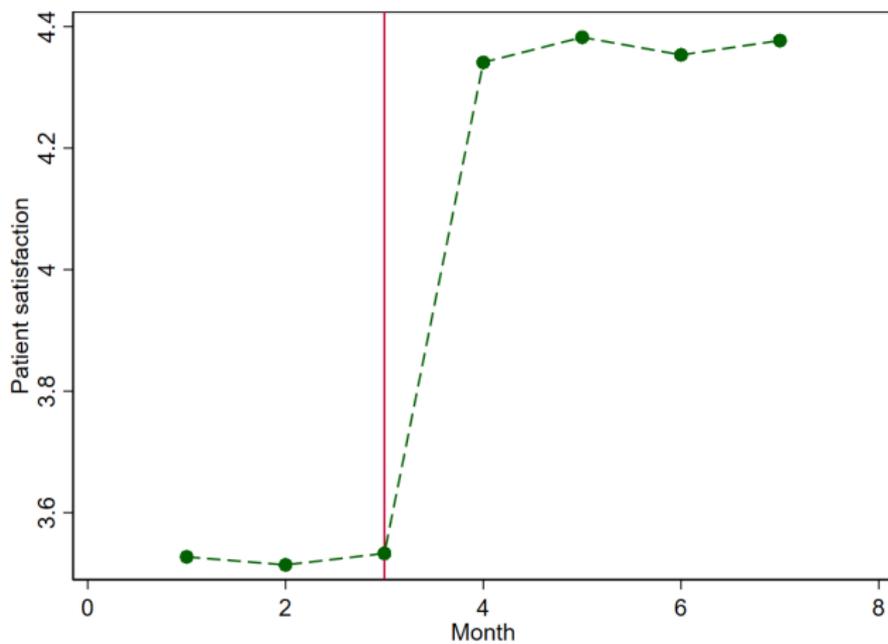
Estimation

```
. 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

Graphical diagnostics for parallel trends
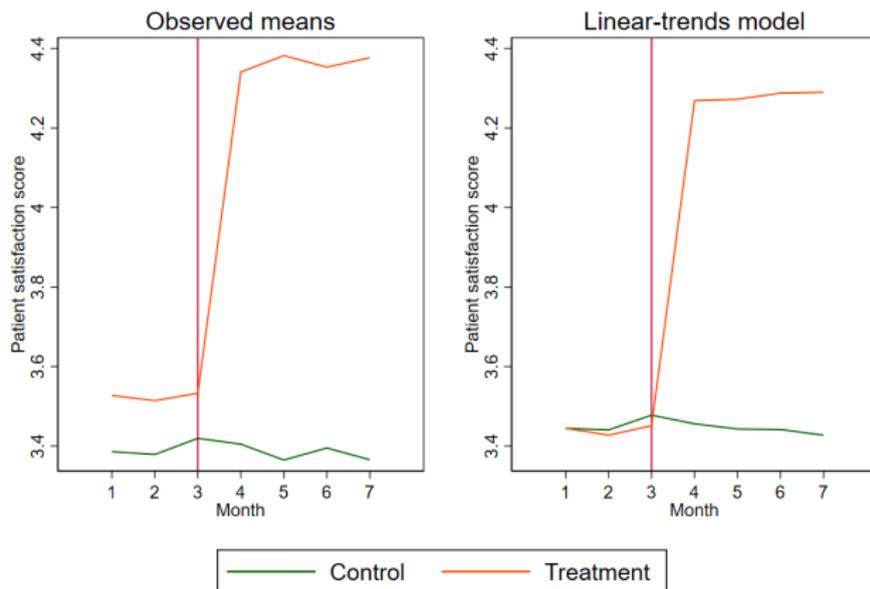
Tests: `estat ptrends`

```
. 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.

estat grangerplot (forthcoming)

Effects over time, leads and lags with 95% CIs
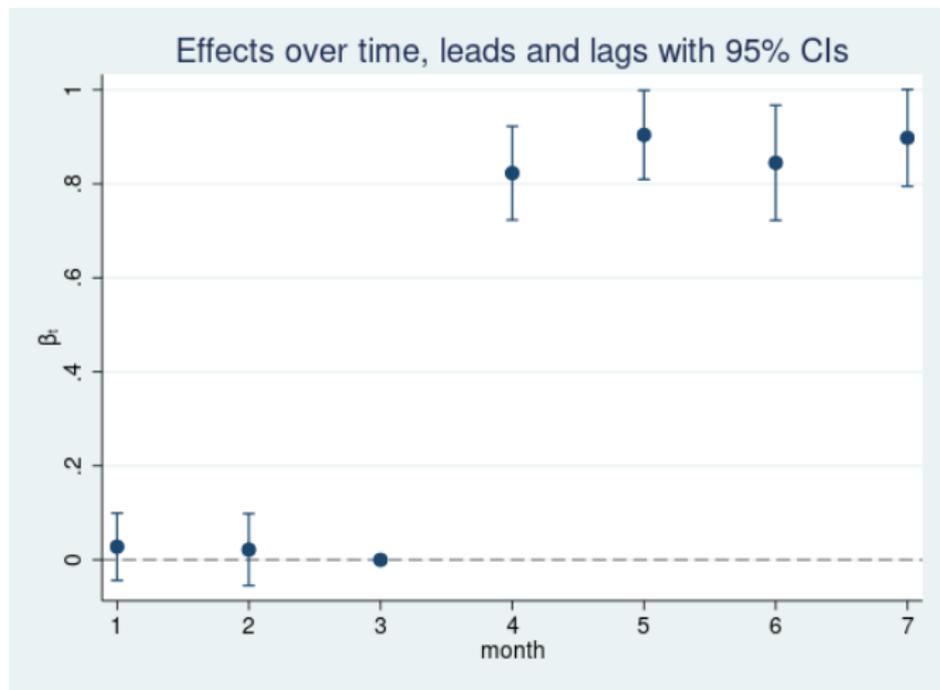
`estat grangerplot, lagview` (forthcoming)

Effects over time, leads and lags with 95% CIs
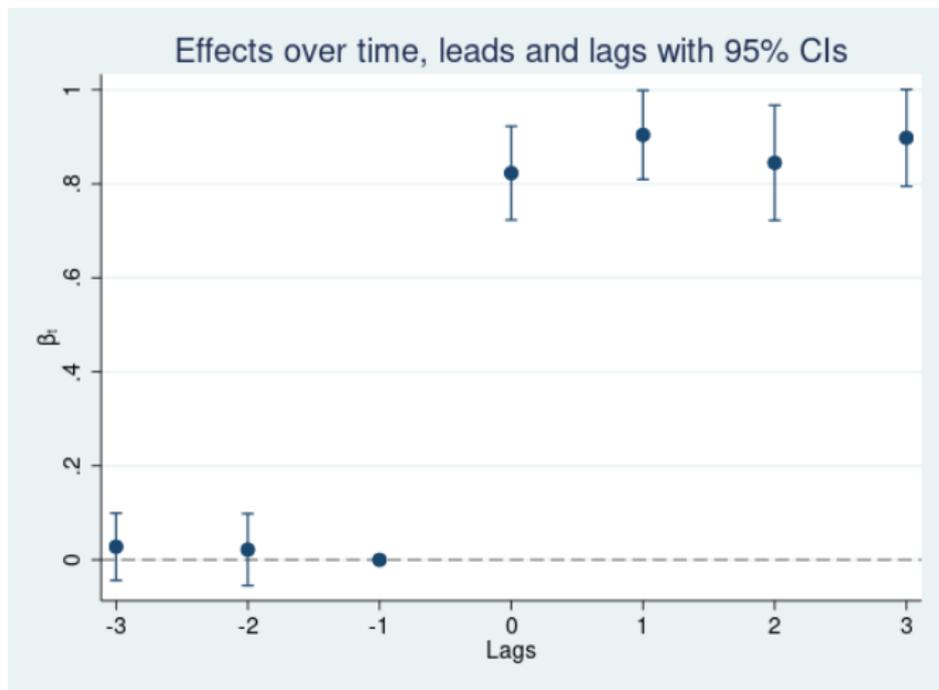
estat grangerplot (results)

```
. estat grangerplot, nodraw verbose
Linear regression, absorbing indicators                    Number of obs   =   7,368
Absorbed variable: hospital                                No. of categories =     46
                                                           F(12, 45)       =   94.68
                                                           Prob > F        =  0.0000
                                                           R-squared       =  0.5334
                                                           Adj R-squared   =  0.5298
                                                           Root MSE        =  0.7240
                                   (Std. err. adjusted for 46 clusters in hospital)
```

satis	Coefficient	Robust std. err.	t	P>|t|	[95% conf. interval]	
month						
February	-.007044	.0263953	-0.27	0.791	-.0602068	.0461188
March	.0335696	.0255696	1.31	0.196	-.0179764	.0851156
April	.0187852	.0250623	0.75	0.457	-.0316927	.0692632
May	-.0211152	.0269569	-0.78	0.438	-.0754092	.0331788
June	.0091208	.0179016	0.51	0.613	-.026935	.0451766
July	-.0203444	.0306266	-0.66	0.510	-.0820296	.0413407
F3_procedure	.027897	.035569	0.78	0.437	-.0437426	.0995367
F2_procedure	.0217322	.0380076	0.57	0.570	-.054819	.0982833
L0_procedure	.8228153	.0494933	16.62	0.000	.7231307	.9224999
L1_procedure	.9040498	.0469682	19.25	0.000	.8094511	.9986486
L2_procedure	.844724	.0608006	13.89	0.000	.7222654	.9671826
L3_procedure	.8978885	.0511588	17.55	0.000	.7948494	1.000928
_cons	3.433074	.0198449	173.00	0.000	3.393104	3.473044

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

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```
. 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
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satis	Coefficient	Robust 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

```
. 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

Wild-cluster bootstrap

- Covariates remain the same across iteration
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- 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
- Speed is substantially improved

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

```
. 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)	Coefficient	t	P>|t|	[95% conf. interval]
	.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.        _cons
                   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 number of observations in the collapsed sample and the number of regressors in z_{2st} and D_{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
```

satis	Coefficient	Robust HC2 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