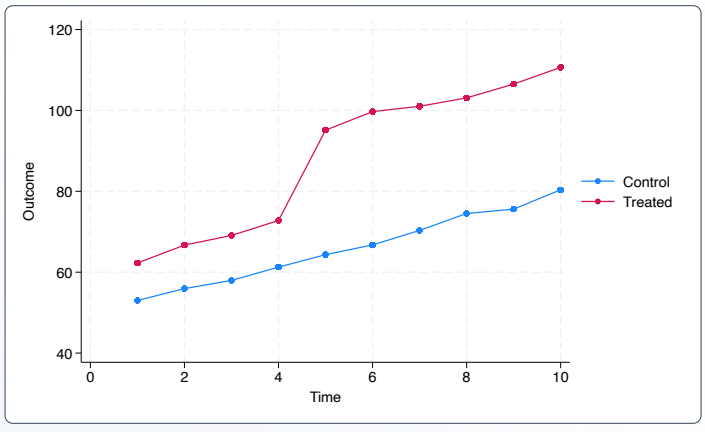
STATA Features

Difference in differences

Difference-in-differences (DID) estimation is one of the most popular methods for causal inference. Stata's **didregress** and **xtdidregress** commands fit DID and triple difference (DDD) models for repeated cross-sectional and panel data. DID and DDD models control for unobserved group and time fixed effects to consistently estimate the average treatment effect on the treated (ATET).

Key assumptions of the models can be tested and graphically displayed via the **estat trendplot**, **estat ptrends**, and **estat granger** commands.

For estimation of ATETs that vary across time and treatment cohorts, you can use Stata's new **hdidregress** and **xthdidregress** commands.



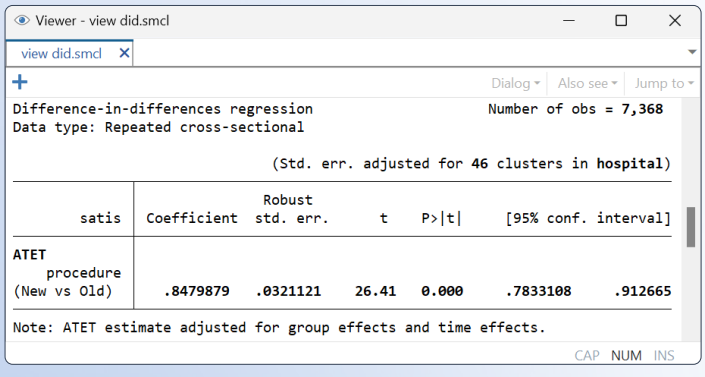
- DID and DDD models for ATET estimation:
  - Repeated cross-sectional data
  - Panel data
- Donald and Lang's aggregation method
- Wild bootstrap *p*-values and confidence intervals
- Bell and McCaffrey's degrees-of-freedom adjustment for bias-corrected standard errors
- Mean-outcome and pretreatment parallel-trends graphical diagnostics
- Granger-type and pretreatment parallel-trends tests
- Heterogeneous DID models New
- Bacon decomposition to assess treatment-effect heterogeneity New

Fit a DID model and estimate ATET

We want to study the effect of a new hospital admissions procedure on patient satisfaction using monthly data on patients before and after the new procedure was implemented by some hospitals.

```
. didregress (satis) (procedure),
              group(hospital) time(month)
```

The ATET of **procedure** on satisfaction was 0.85, accounting for **hospital** and **month** fixed effects. The 95% CI does not include 0.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Dialog · Also see · Jump to

```
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   .0321121    26.41   0.000     .7833108    .912665
------------------------------------------------------------------------------
Note: ATET estimate adjusted for group effects and time effects.
```

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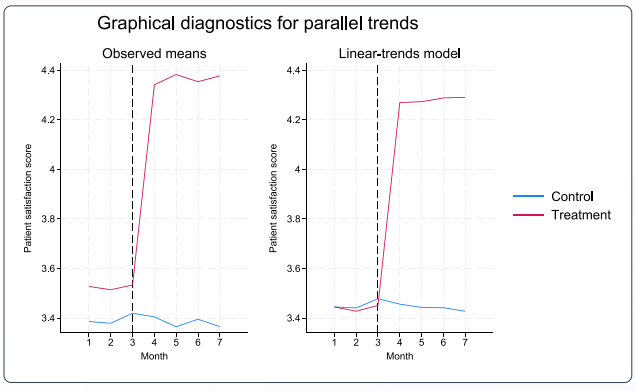
If our data were panel, tell Stata using **xtset** and type

```
. xtdidregress (satis) (procedure),
               group(hospital) time(month)
```

Graphical diagnostics

Our DID model assumes that the trends of **satis** for the control and treatment groups are parallel prior to the implementation of the new procedure. We can obtain a diagnostic of this assumption using **estat trendplot**.



Test for pretreatment parallel trends

We can complement our graphical diagnostic with a formal statistical test using **estat ptrends**.

```
. estat ptrends

Parallel-trends test (pretreatment time period)
H0: Linear trends are parallel

F(1, 45) =   0.55
Prob > F = 0.4615
```

Thus, the null hypothesis of pretreatment parallel trends is not rejected.

Granger causality test

Our DID model also assumes that the treatment and control groups do not change their behavior in anticipation of the treatment. To test this hypothesis, we can implement a Granger causality test using **estat granger**.

```
. estat granger

Granger causality test
H0: No effect in anticipation of treatment

F(2, 45) =   0.33
Prob > F = 0.7239
```

The null hypothesis of no behavior change in anticipation of treatment is not rejected.

A graphical diagnostic is also available using **estat grangerplot**.

Compute appropriate standard errors

It is common to have few groups. In these scenarios, cluster–robust standard errors are unreliable. For such cases, we can use alternative methods to compute standard errors.

We can use HC2 bias-adjusted clustered standard errors by adding the **vce(hc2)** option.

```
. didregress (satis) (procedure),
             group(hostpital) time(month) vce(hc2)
```

We can use the Donald and Lang aggregation method by using the **aggregate(dlang)** option.

```
. didregress (satis) (procedure),
             group(hospital) time(month)
             aggregate(dlang)
```

Wild cluster bootstrap *p*-values and confidence intervals are also available. As with all bootstrap methods, we need to set a seed to make results replicable.

```
. didregress (satis) (procedure),
             group(hospital) time(month)
             wildbootstrap(rseed(123))
```

DDD models

To fit a DDD model, just add another variable to the **group()** option, and define the new treated observations.

```
. didregress (satis) (new_treated),
             group(hospital another_group)
             time(month)
```

Testing for treatment heterogeneity when treatment time varies

If units are treated at different times, the ATET might change for each treatment cohort. If so, DID estimates are inconsistent.

We can inspect ATET heterogeneity after **didregress** and **xtdidregress** using Bacon decomposition by typing

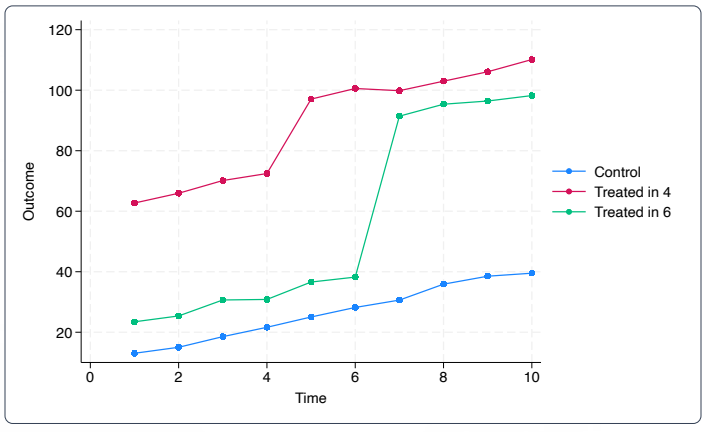
```
. estat bdecomp
```

And we can display the results in a graph by typing

```
. estat bdecomp, graph
```

Heterogeneous DID New

Heterogeneous DID estimates ATETs when treatment effects change over time and are different across cohorts. Use Stata's new **hdidregress** and **xthdidregress** commands to estimate ATETs for each cohort and time period with repeated cross-sectional data and panel data.



- **Estimation of the ATET for each cohort and period**
  - Repeated cross-sectional data
  - Panel data
- **Aggregation of ATETs over**
  - Cohort
  - Period
  - Exposure to treatment
- **Plots and tests of treatment-effect heterogeneity**
- **Simultaneous confidence intervals**
- **Four estimators**
  - Regression adjustment (RA)
  - Inverse-probability weighting (IPW)
  - Augmented inverse-probability weighting (AIPW)
  - Two-way fixed-effects regression (TWFE)
- **Test of pretreatment parallel trends**

Fit a model with heterogeneous treatment effects

We would like to know whether a school district program, Healthy Habits, has an effect on students' body mass index (BMI). Our data are at the school district level and include information on whether a school participates in the program and the BMI of students. We have repeated samples of students from 40 school districts from 2013 to 2020.

We use the **aipw** estimator to model both the outcome and the treatment. We use the number of parks in the district to model treatment and the mother's education to model the outcome.

```
. hdidregress aipw (bmi medu) (hhabit parksd)
                  group(schools) time(year)
```

The AIPW estimator is doubly robust, meaning that, even when the treatment model or the outcome model (but not both) is misspecified, the estimates are still consistent.

Treatment-effect heterogeneity is evident in the results. ATET estimates vary across cohort and time combinations.

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Dialog | Also see | Jump to

```
Heterogeneous treatment-effects regression              Number of obs = 14,896
Estimator:       Augmented IPW
Treatment level: schools
Control group:   Never treated

                                        (Std. err. adjusted for 40 clusters in schools)
------------------------------------------------------------------------------
Cohort       |      ATET   Robust std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
2015         |
        year |
        2014 |   .4383554   .6317095     0.69   0.488    -.7997724    1.676483
        2015 |  -1.148953   .4106347    -2.80   0.005    -1.953783   -.3441241
        2016 |  -2.442539    .389955    -6.26   0.000    -3.206837   -1.678242
        2017 |   -2.47216   .2469231   -10.01   0.000    -2.956121     -1.9882
        2018 |   -2.61101   .6811369    -3.83   0.000    -3.946014   -1.276006
        2019 |  -3.853724   .3430176   -11.23   0.000    -4.526026   -3.181422
        2020 |  -.4349252   .6658255    -0.65   0.514    -1.739919    .8700687
-------------+----------------------------------------------------------------
2017         |
        year |
        2014 |   .5847558   .2734447     2.14   0.032     .048814    1.120698
        2015 |  -1.327894   .4119237    -3.22   0.001    -2.13525   -.5205384
        2016 |   .6134559   .4378406     1.40   0.161    -.244696    1.471608
        2017 |  -1.655656   .4547377    -3.64   0.000    -2.546926   -.7643869
        2018 |  -3.063113   .5123237    -5.98   0.000    -4.067249   -2.058977
        2019 |   -2.95452   .4682755    -6.31   0.000    -3.872324   -2.036717
        2020 |   .1679379   .6764323     0.25   0.804    -1.157845    1.493721
-------------+----------------------------------------------------------------
2019         |
        year |
        2014 |  -1.582866   .5090601    -3.11   0.002    -2.580605   -.5851261
        2015 |   1.189118   .4966923     2.39   0.017     .2156191    2.162617
        2016 |  -.3868035   .4540723    -0.85   0.394    -1.276769    .5031617
        2017 |    .342599   .4860828     0.70   0.481    -.6101058    1.295304
        2018 |   .0661505   .6188046     0.11   0.915    -1.146684    1.278985
        2019 |  -3.733731   .3690283   -10.12   0.000    -4.457013   -3.010448
        2020 |  -1.275938   .6071755    -2.10   0.036     -2.46598   -.0858956
------------------------------------------------------------------------------
Note: ATET computed using covariates.
```

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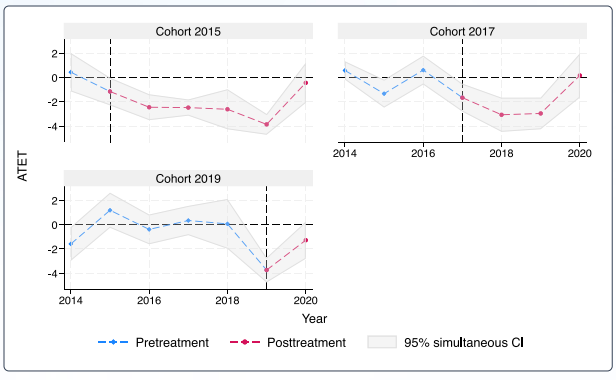
Visualizing ATETs for each cohort

It is difficult to see the trends in ATETs just by looking at all the ATETs estimates. We can use **estat atetplot** to visualize the time profile of ATETs for each cohort. We specify the **sci** option to show the simultaneous confidence bands that cover the true values of ATETs across all the cohorts and times with the predefined probability level.

```
. estat atetplot, sci
```



Aggregating ATETs

After fitting the model, we can use **estat aggregation** to aggregate the ATETs within cohort, time, or exposure to treatment. For example, we use **estat aggregation, cohort** to summarize the ATETs within each cohort.

```
. estat aggregation, cohort graph
```

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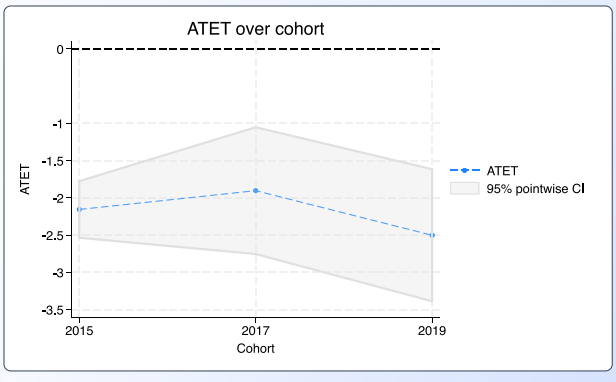
ATET over cohort Number of obs = 14,896

(Std. err. adjusted for 40 clusters in schools)

Cohort	ATET	Robust std. err.	z	P>|z|	[95% conf.	interval]
2015	-2.155574	.1938914	-11.12	0.000	-2.535594	-1.775553
2017	-1.902833	.4342688	-4.38	0.000	-2.753984	-1.051682
2019	-2.502028	.4523586	-5.53	0.000	-3.388635	-1.615422



If we want to summarize ATETs within time, we specify the **time** option with **estat aggregation**.

```
. estat aggregation, time graph
```

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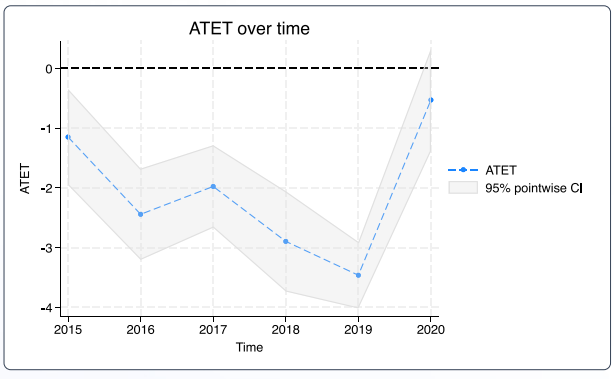
ATET over time Number of obs = 14,896

(Std. err. adjusted for 40 clusters in schools)

Time	ATET	Robust std. err.	z	P>|z|	[95% conf.	interval]
2015	-1.148953	.4106347	-2.80	0.005	-1.953783	-.3441241
2016	-2.442539	.389955	-6.26	0.000	-3.206837	-1.678242
2017	-1.976693	.3520842	-5.61	0.000	-2.666766	-1.286621
2018	-2.896058	.4285858	-6.76	0.000	-3.736071	-2.056046
2019	-3.462559	.2844555	-12.17	0.000	-4.020081	-2.905036
2020	-.5284933	.4388922	-1.20	0.229	-1.388706	.3317196



Finally, if we want to summarize ATETs within different lengths of exposure to treatment, we specify option **dynamic**.

```
. estat aggregation, dynamic graph
```

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Duration of exposure ATET Number of obs = 14,896

(Std. err. adjusted for 40 clusters in schools)

Exposure	ATET	Robust std. err.	z	P>|z|	[95% conf.	interval]
-5	-1.582866	.5090601	-3.11	0.002	-2.580605	-.5851261
-4	1.189118	.4966923	2.39	0.017	.2156191	2.162617
-3	.0920222	.3036811	0.30	0.762	-.5031817	.6872262
-2	-.4830067	.4073054	-1.19	0.236	-1.281311	.3152972
-1	.3637212	.3316411	1.10	0.273	-.2862834	1.013726
0	-2.291459	.4127642	-5.55	0.000	-3.100462	-1.482455
1	-2.24827	.3637353	-6.18	0.000	-2.961178	-1.535362
2	-2.762854	.3028096	-9.12	0.000	-3.35635	-2.169358
3	-.8969296	.6722539	-1.33	0.182	-2.214523	.4206639
4	-3.853724	.3430176	-11.23	0.000	-4.526026	-3.181422
5	-.4349252	.6658255	-0.65	0.514	-1.739919	.8700687

Note: Exposure is the number of periods since the first treatment time.