**xthdidpoisson** — Heterogeneous difference-in-differences panel-data Poisson regression[+]

[+]This command is part of StataNow.


Description | Quick start | Menu | Syntax
Options | Remarks and examples | Stored results | Methods and formulas
Acknowledgments | References | Also see


## Description

`xthdidpoisson` estimates average treatment effects on the treated (ATETs) that may vary over time and over treatment cohorts for nonnegative and count outcomes by using pooled Poisson regression.

## Quick start

Estimate ATETs of treatment `treat` on count outcome `y` with group `grpvar`, and model `y` with covariate `x` on `xtset` data

```
xthdidpoisson (y x) (treat), group(grpvar)
```

Same as above, but use user-provided cohort variable `mycohort` instead of letting the command generate a cohort variable

```
xthdidpoisson (y x) (treat), group(grpvar) usercohort(mycohort)
```

Same as above, but use the not-yet-treated group as the control group

```
xthdidpoisson (y x) (treat), group(grpvar) controlgroup(notyet) ///
    usercohort(mycohort)
```

Same as above, but without including interactions between covariates and the treatment or interactions between covariates and the cohort variable

```
xthdidpoisson (y x) (treat), group(grpvar) controlgroup(notyet) ///
    usercohort(mycohort) noxinteract
```

## Menu

Statistics > Causal inference/treatment effects > Count outcomes > Panel-data heterogeneous DID

# Syntax

```
xthdidpoisson (ovar [omvarlist]) (tvar) [if] [in] [weight], group(groupvar) [options]
```

*ovar* is a nonnegative or count outcome of interest.

*omvarlist* specifies the covariates in the outcome model and may contain factor variables; see **[U] 11.4.3 Factor variables**.

*tvar* must be a binary variable indicating observations subject to treatment.

*groupvar* is a categorical variable that indicates the group level at which the treatment occurs.

| *options* | Description |
|---|---|
| Model | |
| * `group(`*groupvar*`)` | specify group variable |
| `controlgroup(`*cgtype*`)` | specify the type of control group; default is `controlgroup(never)` |
| `cohortvar(`*cvar*`[ , replace ])` | specify the name for the generated cohort variable |
| `usercohort(`*varname*`)` | specify the name of the cohort variable to be used for estimation |
| `hettype(`*hetspec*`)` | specify the type of heterogeneity; default is `hettype(timecohort)` |
| `over(`*overspec*`)` | specify the subpopulation over which each ATET is computed; default is `over(cohort)` |
| `noxinteract` | omit covariate interactions |
| SE/Robust | |
| `vce(`*vcetype*`)` | *vcetype* may be `cluster` *clustvar*, `robust`, `bootstrap`, or `jackknife` |
| Reporting | |
| `level(#)` | set confidence level; default is `level(95)` |
| *display_options* | control columns and column formats, row spacing, line width, display of omitted variables and base and empty cells, and factor-variable labeling |
| `coeflegend` | display legend instead of statistics |

| *cgtype* | Description |
|---|---|
| `never` | use the never-treated group as the control group; the default |
| `notyet` | use the not-yet-treated group as the control group |

| *hetspec* | Description |
|---|---|
| `timecohort` | heterogeneous treatment effects over time and cohort; the default |
| `time` | heterogeneous treatment effects over time |
| `cohort` | heterogeneous treatment effects over cohort |

| *overspec* | Description |
|---|---|
| `cohort` | use cohort subpopulations when controlling for covariate heterogeneity; the default |
| `timecohort` | use time and cohort subpopulations when controlling for covariate heterogeneity |

*`group()` is required.

A panel variable and a time variable must be specified using `xtset`; see [XT] **xtset**.

`by`, `collect`, and `statsby` are allowed; see **[U] 11.1.10 Prefix commands**.

`fweights`, `iweights`, and `pweights` are allowed; see **[U] 11.1.6 weight**. Weights must be constant within panel.

`coeflegend` does not appear in the dialog box.

See **[U] 20 Estimation and postestimation commands** for more capabilities of estimation commands.

# Options

Model

`group(`*groupvar*`)` specifies a group variable that indicates the group level at which the treatment occurs. *groupvar* may be, for example, states, counties, or hospitals. `group()` also defines the clusters for the default cluster–robust standard errors. `group()` is required. You may specify only one group variable.

`controlgroup(`*cgtype*`)` specifies the type of control group. A control group can be either a never-treated group or a not-yet-treated group. A never-treated group refers to the units that are untreated from the first to the last period. A not-yet-treated group refers to the units that are untreated up to a specific period. *cgtype* can be one of `never`, referring to the never-treated group, or `notyet`, referring to the not-yet-treated group. The default is `controlgroup(never)`.

`cohortvar(`*cvar*`[ , replace ])` specifies the variable name *cvar* for the generated cohort variable. The cohort variable is a categorical variable indicating the period when the unit is first treated. By default, `_did_cohort` is used as the name of the cohort variable. If `_did_cohort` already exists in the dataset, it is replaced if the `cohortvar()` option is not specified.

If the `replace` suboption is specified, *cvar* is replaced.

`usercohort(`*varname*`)` specifies a variable to be used as a cohort indicator during estimation. By default, a cohort variable is generated using the information in the estimation sample to indicate the period when a unit is first treated. `usercohort()` overrides this default and allows you to provide a cohort indicator. This is useful, for instance, when there are gaps in the estimation sample, but you know a group was treated at the time when the gap is present in the data.

`hettype(`*hetspec*`)` specifies time or cohort heterogeneity for the `twfe` estimator. By default, treatment is interacted with time and cohort. You may choose to keep one of time or cohort interactions using *hetspec*.

*hetspec* may be one of `timecohort` for heterogeneous treatment effects over both time and cohort, `time` for heterogeneous treatment effects over time only, or `cohort` for heterogeneous treatment effects over cohort only. The default is `hettype(timecohort)`.

over(*overspec*) specifies the subpopulation over which treatment effects are averaged. When covariates are specified, you need to control for their variation when computing treatment effects. The default is over(cohort), meaning effects are averaged over each cohort and adjusted for the time period effect. If there are no covariates, this option has no effect.

When the heterogeneity type is specified as timecohort (hettype(timecohort)), *overspec* may be one of cohort for effects averaged over each cohort or timecohort for effects averaged over each time period and cohort.

When the heterogeneity type is specified as cohort (hettype(cohort)), *overspec* may only be cohort for effects averaged over each cohort.

over() may not be specified with hettype(time).

noxinteract specifies that the covariates in *omvarlist* not be interacted with the difference-in-differences regressors. Covariates are still included in the model as levels.

SE/Robust

vce(*vcetype*) specifies the type of standard error reported, which includes types that allow for intragroup correlation (cluster *clustvar*), that are robust to intragroup correlation among group variable (robust), and that use bootstrap or jackknife sampling done at the panel level (bootstrap, jackknife); see [R] ***vce_option***.

vce(cluster *clustvar*), the default, uses the variable specified in group(*groupvar*).

Specifying vce(robust) is equivalent to specifying vce(cluster *clustvar*), where *clustvar* is the variable specified in the group(*groupvar*) option.

Reporting

level(#); see [R] **Estimation options**.

*display_options*: noci, nopvalues, cformat(%*fmt*), pformat(%*fmt*), sformat(%*fmt*), and nolstretch; see [R] **Estimation options**.

The following option is available with xthdidpoisson but is not shown in the dialog box:

coeflegend; see [R] **Estimation options**.

## Remarks and examples

It is common to study the effects of a treatment, for example, a policy or intervention, on a group. xthdidpoisson is for data where the treated groups are subject to the treatment at different points in time and they remain exposed to the treatment. Outcomes here may be nonnegative or counts because xthdidpoisson fits exponential-mean models.

xthdidpoisson estimates ATET parameters that change over time and treatment cohorts (groups treated at different points in time). Each one of these ATETs has the same interpretation that the parameters of a two-time, two-group difference-in-differences (DID) parameter would have. Because there are multiple DID parameters, we refer to them as heterogeneous treatment effects or as heterogeneous DID. This contrasts with estimating only one ATET, which assumes there is no variation across time or cohort. If you assume no variation across time or cohort and you do not want to model the outcome as having an exponential mean, you may use xtdidregress; see [CAUSAL] **didregress**.

xthdidpoisson implements a pooled Poisson estimator described in Wooldridge (2023). It fits a cross-sectional model in which the treatment is interacted with time, cohort, and covariates. This approach allows you to incorporate treatment heterogeneity at all the aforementioned levels. Covariate interactions allow you to explore moderating effects (how the treatment effect is affected by covariates) by using the estat moderation postestimation command. Cohort and time interactions allow you to explore heterogeneity within time and cohort by using estat aggregation, time and estat aggregation, cohort. You may also want to explore how treatment effects evolve by using estat aggregation, dynamic.

For treatment effects to be identified in a DID framework, a parallel-trends assumption needs to be satisfied; see [CAUSAL] **DID intro**. In the linear case, fit using xthdidregress twfe, the parallel-trends assumption is satisfied for the linear prediction, $\mathbf{x}\beta$, of the potential outcomes. The linear prediction is, by construction, a one-to-one mapping of the conditional mean in that case. For nonlinear DID, you can think about the parallel-trends assumption as being satisfied either for conditional means or for the linear prediction but not for both. For the estimator implemented in xthdidpoisson, the identification relies on parallel trends for the linear prediction as proposed by Wooldridge (2023). You may use estat ptrends to evaluate this assumption.

## Example 1: Fitting a Poisson heterogeneous DID model

We are interested in the causal relation between the number of weekly accidents per capita, accidents, in a college town and the appearance of scooters for rent in town, scooter. We have fictional data for 432 college towns from the years 2015 to 2024. Scooter rental becomes available in different years at the different college towns, starting in 2017.

To obtain the effect of scooter on accidents, we first xtset our panel dataset:

```
. use https://www.stata-press.com/data/r19/scooters
(Fictional data of accidents on college campuses)
. xtset id year
Panel variable: id (strongly balanced)
 Time variable: year, 2015 to 2024
         Delta: 1 unit
```

We fit the model with the xthdidpoisson command. In the first set of parentheses, we declare the outcome and any covariates that affect the outcome directly. In the second set of parentheses, we define the observation-level treatment variable. After the comma, we need to define the group variable in group(), which is required. The group variable defines at which level the treatment occurs and also identifies the clustering variable, which in this case is id. The command and results are as follows:

```
. xthdidpoisson (accidents) (scooter), group(id)
note: variable _did_cohort, containing cohort indicators formed by treatment
      variable scooter and group variable id, was added to the dataset using
      the estimation sample.
Computing ATETs using margins ...
```

Treatment and time information

Time variable: year
Time interval: 2015 to 2024
Control: _did_cohort = 0
Treatment: _did_cohort > 0

| | _did_cohort |
|---|---|
| Number of cohorts | 5 |
| Number of obs | |
| Never treated | 2650 |
| 2017 | 480 |
| 2019 | 370 |
| 2021 | 400 |
| 2022 | 420 |

Heterogeneous-treatment-effects Poisson regression — Number of obs = 4,320; Number of panels = 432

Panel variable: id
Treatment level: id
Control group: Never treated
Heterogeneity: Cohort and time

(Std. err. adjusted for 432 clusters in id)

| Cohort | | ATET | Robust std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|---|
| 2017 | | | | | | | |
| | year | | | | | | |
| | 2017 | .5619206 | .1886505 | 2.98 | 0.003 | .1921724 | .9316688 |
| | 2018 | .6725162 | .1664993 | 4.04 | 0.000 | .3461837 | .9988488 |
| | 2019 | .9550554 | .2042622 | 4.68 | 0.000 | .5547089 | 1.355402 |
| | 2020 | .8113546 | .1794331 | 4.52 | 0.000 | .4596723 | 1.163037 |
| | 2021 | 1.25579 | .2190781 | 5.73 | 0.000 | .8264046 | 1.685175 |
| | 2022 | 1.376403 | .1862243 | 7.39 | 0.000 | 1.01141 | 1.741396 |
| | 2023 | 1.508712 | .1845332 | 8.18 | 0.000 | 1.147034 | 1.870391 |
| | 2024 | 1.714412 | .1826261 | 9.39 | 0.000 | 1.356472 | 2.072353 |
| 2019 | | | | | | | |
| | year | | | | | | |
| | 2019 | 1.580742 | .1484523 | 10.65 | 0.000 | 1.289781 | 1.871703 |
| | 2020 | 1.76987 | .1943237 | 9.11 | 0.000 | 1.389003 | 2.150738 |
| | 2021 | 2.190438 | .1933796 | 11.33 | 0.000 | 1.811421 | 2.569455 |
| | 2022 | 2.859944 | .223045 | 12.82 | 0.000 | 2.422784 | 3.297104 |
| | 2023 | 2.876892 | .1746983 | 16.47 | 0.000 | 2.53449 | 3.219294 |
| | 2024 | 3.248025 | .1848912 | 17.57 | 0.000 | 2.885645 | 3.610405 |
| 2021 | | | | | | | |
| | year | | | | | | |
| | 2021 | 3.334094 | .1892891 | 17.61 | 0.000 | 2.963094 | 3.705093 |
| | 2022 | 4.07135 | .2047359 | 19.89 | 0.000 | 3.670075 | 4.472625 |
| | 2023 | 4.440213 | .1808275 | 24.55 | 0.000 | 4.085798 | 4.794629 |
| | 2024 | 5.064493 | .2098745 | 24.13 | 0.000 | 4.653147 | 5.47584 |
| 2022 | | | | | | | |
| | year | | | | | | |
| | 2022 | 2.391159 | .2251628 | 10.62 | 0.000 | 1.949848 | 2.83247 |
| | 2023 | 2.707001 | .2013972 | 13.44 | 0.000 | 2.312269 | 3.101732 |
| | 2024 | 2.936917 | .2140572 | 13.72 | 0.000 | 2.517373 | 3.356462 |

Notice the note below the command. A variable with the name _did_cohort has been generated. Looking at the group variable and the observation-level treatment, xthdidpoisson detected we have treatment-time cohorts. The new variable creates treatment groups based on the time when a group was first treated. For instance, if scooter rentals appear in a college town in 2017, that college town is grouped into the 2017 cohort. The variable also contains a category for a control group. In this case, the control group is formed by the college towns where, during the period of analysis, scooters never became available for rent.

Cohorts are an important input for estimation and for postestimation commands. We do not need to adhere to the default name, _did_cohort, and may provide our own name by using the cohortvar() option. Also, we do not need to rely on xthdidpoisson creating the cohort based on the estimation sample; instead, we might provide a cohort indicator we created or which is already in our dataset by using the usercohort() option. We illustrate this in example 2 below.

Next appears a table that gives us a sense of the treatment groups and time. We see the time variable, year, and its range, 2015 to 2024. Then we see what defines a treated or a control group. The table below provides group-level information about the cohort-time groups. The first row tells us the number of cohorts. Following the number of cohorts is a tabulation showing how many observations are in each cohort. For instance, 2,650 observations are never treated in our dataset. The table gives us a sense of the amount of information available in each cohort and might hint at the variability of cohort-level estimates.

The next table presents the ATET estimates. The first panel shows the ATETs for the 2017 cohort. We first have the 2017 ATET of 0.56, with a confidence interval that does not include 0. We should interpret the ATET to mean that, among the college towns that had availability of scooters starting in 2017, the expected weekly accidents per capita, accidents, in 2017 were 0.56 higher than if the college town had not had scooter rentals available. In 2018, we observe a treatment effect for the number of accidents of 0.67, and on the last year of our data for the 2017 cohort, we see a treatment effect of 1.71. We interpret the results for the remaining cohorts similarly.

◁

## ▷ Example 2: User-provided cohort variable and missing data

We would like to control for the average level of fines for traffic violations in a college town. We believe that higher fines are a deterrent to risky traffic behavior and that this affects the number of accidents.

Before including a variable in our model, we need to check how it modifies our estimation sample, because xthdidpoisson constructs the _did_cohort variable based on it. For instance, if a college town is treated from 2017 to 2024 but a covariate for that id has a missing value for the year 2017, that year will be excluded from the estimation sample for that town. The _did_cohort variable will then consider that college town as being part of the 2018 cohort. This is the case because, in the estimation sample, 2018 is the first year for which the group is treated. Before including the variable fines, we should examine how it compares with the other variables in our model in terms of the number of observations:

```
. summarize id year scooter fines
```

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| id | 4,320 | 216.5 | 124.7218 | 1 | 432 |
| year | 4,320 | 2019.5 | 2.872614 | 2015 | 2024 |
| scooter | 4,320 | .2064815 | .4048269 | 0 | 1 |
| fines | 3,673 | 1.889151 | .4453375 | 1.015038 | 3.798207 |

Introducing `fines` will result in a loss of 15% of our sample, a sizable difference. In such cases, we recommend using the `gencohort` command. We type

```
. gencohort mycohort, group(id) time(year) treat(scooter)
```

Of course, `mycohort` is the same as the cohort variable we obtained in example 1, but in this case, we can avoid dropping observations by creating it ourselves.

We now fit the model controlling for `fines`.

```
. xthdidpoisson (accidents fines) (scooter), group(id) usercohort(mycohort)
note: variable _did_cohort, containing a copy of the variable specified in
      usercohort() for this estimation sample, was added to the dataset.

Computing ATETs using margins ...

Treatment and time information

Time variable: year
Time interval: 2015 to 2024
Control:       _did_cohort = 0
Treatment:     _did_cohort > 0
```

| | _did_cohort |
|---|---|
| Number of cohorts | 5 |
| Number of obs | |
| Never treated | 2249 |
| 2017 | 390 |
| 2019 | 317 |
| 2021 | 345 |
| 2022 | 356 |

```
Heterogeneous-treatment-effects Poisson regression    Number of obs    = 3,657
                                                      Number of panels =   430
Panel variable:  id
Treatment level: id
Control group:   Never treated
Heterogeneity:   Cohort and time
                                        (Std. err. adjusted for 430 clusters in id)
```

| Cohort | ATET | Robust std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| 2017 | | | | | | |
| year | | | | | | |
| 2017 | .5335946 | .2168946 | 2.46 | 0.014 | .1084891 | .9587002 |
| 2018 | .779348 | .1821991 | 4.28 | 0.000 | .4222444 | 1.136452 |
| 2019 | 1.008465 | .2171924 | 4.64 | 0.000 | .5827753 | 1.434154 |
| 2020 | .977643 | .1941842 | 5.03 | 0.000 | .597049 | 1.358237 |
| 2021 | 1.295613 | .2374521 | 5.46 | 0.000 | .8302154 | 1.76101 |
| 2022 | 1.500081 | .2152936 | 6.97 | 0.000 | 1.078113 | 1.922049 |
| 2023 | 1.595877 | .2085629 | 7.65 | 0.000 | 1.187101 | 2.004652 |
| 2024 | 1.761608 | .1855263 | 9.50 | 0.000 | 1.397983 | 2.125233 |
| 2019 | | | | | | |
| year | | | | | | |
| 2019 | 1.600723 | .1745367 | 9.17 | 0.000 | 1.258638 | 1.942809 |
| 2020 | 1.888832 | .1831422 | 10.31 | 0.000 | 1.52988 | 2.247784 |
| 2021 | 2.075027 | .2059444 | 10.08 | 0.000 | 1.671384 | 2.478671 |
| 2022 | 2.735224 | .220631 | 12.40 | 0.000 | 2.302795 | 3.167653 |
| 2023 | 2.605346 | .1523015 | 17.11 | 0.000 | 2.30684 | 2.903851 |
| 2024 | 3.224554 | .1699647 | 18.97 | 0.000 | 2.891429 | 3.557679 |
| 2021 | | | | | | |
| year | | | | | | |
| 2021 | 3.401506 | .1725441 | 19.71 | 0.000 | 3.063326 | 3.739686 |
| 2022 | 3.99764 | .2010873 | 19.88 | 0.000 | 3.603516 | 4.391764 |
| 2023 | 4.447965 | .1531321 | 29.05 | 0.000 | 4.147831 | 4.748098 |
| 2024 | 4.969777 | .1547503 | 32.11 | 0.000 | 4.666472 | 5.273082 |
| 2022 | | | | | | |
| year | | | | | | |
| 2022 | 2.287949 | .1854099 | 12.34 | 0.000 | 1.924552 | 2.651346 |
| 2023 | 2.868844 | .1840671 | 15.59 | 0.000 | 2.50808 | 3.229609 |
| 2024 | 3.009002 | .1935608 | 15.55 | 0.000 | 2.62963 | 3.388375 |

```
Note: ATET computed using covariates.
```

The results did not change substantively from the previous example. Also, the cohort information is consistent with the model without `fines`.

◁

## Example 3: Moderating effects

Because the model we fit is a pooled Poisson regression with interactions between treatment and covariates, we can explore how the treatment effects change when covariate values change: a moderating effect. We do this below:

```
. estat moderation
Moderating effects                                      Number of obs = 3,657
                                   (Std. err. adjusted for 430 clusters in id)
```

| | Effect | Robust std. err. | z | P>\|z\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| fines | | | | | | |
| _did_cohort# year | | | | | | |
| 2017 2017 | -.6946721 | .5236282 | -1.33 | 0.185 | -1.720964 | .3316202 |
| 2017 2018 | -.4432957 | .2998815 | -1.48 | 0.139 | -1.031053 | .1444613 |
| 2017 2019 | -.7746514 | .3849958 | -2.01 | 0.044 | -1.529229 | -.0200734 |
| 2017 2020 | -.7788583 | .4086064 | -1.91 | 0.057 | -1.579712 | .0219954 |
| 2017 2021 | -.9832937 | .446157 | -2.20 | 0.028 | -1.857745 | -.1088421 |
| 2017 2022 | -.8743209 | .4371464 | -2.00 | 0.045 | -1.731112 | -.0175298 |
| 2017 2023 | -.5197772 | .5139391 | -1.01 | 0.312 | -1.527079 | .4875249 |
| 2017 2024 | -.4558528 | .4000268 | -1.14 | 0.254 | -1.239891 | .3281854 |
| 2019 2019 | .5057996 | .4472233 | 1.13 | 0.258 | -.370742 | 1.382341 |
| 2019 2020 | -.5894671 | .4979056 | -1.18 | 0.236 | -1.565344 | .38641 |
| 2019 2021 | -1.057017 | .4914579 | -2.15 | 0.031 | -2.020257 | -.0937774 |
| 2019 2022 | -.4312658 | .3842573 | -1.12 | 0.262 | -1.184396 | .3218646 |
| 2019 2023 | -.7930585 | .3217355 | -2.46 | 0.014 | -1.423648 | -.1624685 |
| 2019 2024 | -.454865 | .4081156 | -1.11 | 0.265 | -1.254757 | .345027 |
| 2021 2021 | -1.005237 | .3062045 | -3.28 | 0.001 | -1.605387 | -.405087 |
| 2021 2022 | -.8997555 | .4077756 | -2.21 | 0.027 | -1.698981 | -.10053 |
| 2021 2023 | -.7700024 | .3161676 | -2.44 | 0.015 | -1.389679 | -.1503252 |
| 2021 2024 | -1.128937 | .4184218 | -2.70 | 0.007 | -1.949029 | -.3088452 |
| 2022 2022 | -1.340634 | .4353701 | -3.08 | 0.002 | -2.193944 | -.4873246 |
| 2022 2023 | -1.837942 | .477821 | -3.85 | 0.000 | -2.774454 | -.9014303 |
| 2022 2024 | -1.340999 | .3149278 | -4.26 | 0.000 | -1.958247 | -.7237522 |

An increase in `fines` reduces the treatment effect for the 2021 and 2022 cohorts. For the other cohorts, there is also a negative effect, but it is not always different from zero.

# Stored results

xthdidpoisson stores the following in e():

Scalars

| | |
|---|---|
| e(N) | number of observations |
| e(N_clust) | number of clusters |
| e(N_panels) | number of panels |
| e(tmin) | first time period |
| e(tmax) | last time period |
| e(rank) | rank of e(V) |
| e(xinteract) | 1 if covariate interactions are included, 0 otherwise |

Macros

| | |
|---|---|
| e(cmd) | xthdidpoisson |
| e(cmdline) | command as typed |
| e(depvar) | name of outcome variable |
| e(clustvar) | name of cluster variable |
| e(control_group) | control group |
| e(het_type) | heterogeneity type |
| e(over_type) | subpopulation over which each ATET is computed |
| e(cohortvar) | name of cohort variable |
| e(usercohort) | name of user-specified cohort variable |
| e(ovar) | name of outcome variable |
| e(wtype) | weight type |
| e(wexp) | weight expression |
| e(marginsnotok) | predictions disallowed by margins |
| e(ivar) | panel identifier variable |
| e(timevar) | time variable |
| e(treatname) | name of treatment variable |
| e(estat_cmd) | program used to implement estat |
| e(vce) | *vcetype* specified in vce() |
| e(vcetype) | title used to label Std. err. |
| e(properties) | b V |

Matrices

| | |
|---|---|
| e(b) | coefficient vector |
| e(V) | variance–covariance matrix of the estimators |
| e(cohort_count) | matrix with cohort count information |

Functions

| | |
|---|---|
| e(sample) | marks estimation sample |

In addition to the above, the following is stored in r():

Matrices

| | |
|---|---|
| r(table) | matrix containing the coefficients with their standard errors, test statistics, *p*-values, and confidence intervals |

Note that results stored in r() are updated when the command is replayed and will be replaced when any r-class command is run after the estimation command.

# Methods and formulas

Methods and formulas are presented under the following headings:

*The model*
*The pooled Poisson estimator*

## The model

Denote $y_{it}(g)$ as the potential outcome for unit $i$ at time $t$ if it was first treated at time $g$. Denote $y_{it}(0)$ as the potential outcome for unit $i$ at time $t$ if it is never treated. All the units can be grouped into cohorts, and the units of each cohort start the treatment simultaneously. For example, cohort $g$ means all the units start treatment at time $g$. Let $G_{ig}$ be an indicator that equals 1 if unit $i$ is first treated at time $g$. Then the units in cohort $g$ can be denoted by $G_{ig} = 1$. When a unit $i$ is never treated, we denote $G_{i0} = 1$. Thus, cohort 0 indicates all the units that are never treated. We assume that once a unit is treated, it will remain treated.

To reveal how the heterogeneous treatment effects evolve across cohorts and time, we are interested in estimating the ATET for each combination of cohort and time. Let $\theta(g,t)$ be the ATET for cohort $g$ at time $t$, which is defined as

$$\theta(g,t) = \mathbf{E}\left\{y_t(g) - y_t(0) | G_g = 1\right\} \tag{ATET}$$

where $G_g$ equals 1 if a unit belongs to cohort $g$. We use `margins` to estimate $\theta(g,t)$ in equation (ATET). We cannot directly estimate $\theta(g,t)$ by using equation (ATET) because the potential outcomes $y_t(g)$ and $y_t(0)$ are not observable.

## The pooled Poisson estimator

We estimate the parameters of the model by using pooled Poisson regression; see [R] **poisson**. The model can be thought of in terms of an exponential mean given by

$$\begin{aligned} E\left(y_{it}|\mathbf{x}_i, d_{it}, G_{ig}, f_s\right) = \exp\Big(&\eta + \sum_{g=q}^{T} G_{ig}\alpha_g + \sum_{s=q}^{T} f_s\gamma_s + \sum_{g=q}^{T}\sum_{s=g}^{T} d_{it}G_{ig}f_s\tau_{gs} + \sum_{g=q}^{T} G_{ig}\mathbf{x}_i\boldsymbol{\alpha}_g^{\mathbf{x}} \\ &+ \sum_{s=q}^{T} f_s\mathbf{x}_i\boldsymbol{\gamma}_s^{\mathbf{x}} \sum_{g=q}^{T}\sum_{s=g}^{T} d_{it}G_{ig}f_s\mathbf{x}_i\boldsymbol{\tau}_{gs}^{\mathbf{x}} + \mathbf{x}_{it}\boldsymbol{\beta}\Big) \end{aligned} \tag{EXP}$$

The terms on the right-hand side of equation (EXP) are the regressors in the model for which the cohort-time treatment effects are a function of $\tau_{gs}$, $\boldsymbol{\tau}_{gs}^{\mathbf{x}}$, and the covariates. In equation (EXP), $d_{it}$ is a treatment indicator, and $f_s$ represents an indicator for posttreatment periods with $s$ going from $q$ to $T$, where $q$ is the first time period we observe treatment. For instance, $f_q$ equals 1 if we are in time period $q$ and 0 otherwise. We can compute these effects using `margins` by typing

```
. margins, dydx(d) at(year=q ... year=T) over(cohort) vce(unconditional)
```

where `d` is the treatment indicator, `year` indicates treatment times at which treatment will be evaluated using `at()`, and `cohort` is the treatment-time cohorts.

If `over(timecohort)` was specified with `xthdidpoisson`, we can obtain effects by typing

```
. margins, dydx(d) over(year cohort) vce(unconditional)
```

We use `vce(unconditional)` to account for the variation in the covariates. When there are no covariates specified or when `noxinteract` is specified, `vce(unconditional)` has no effect. Furthermore, if we include covariates but specify `noxinteract`, our equation reduces to

$$E\left(y_{it}|\mathbf{x}_{it},d_{it},G_{ig},f_s\right) = \exp\Big(\eta+\sum_{g=q}^{T}G_{ig}\alpha_g+\sum_{s=q}^{T}f_s\gamma_s+\sum_{g=q}^{T}\sum_{s=g}^{T}d_{it}G_{ig}f_s\tau_{gs}+\mathbf{x}_{it}\boldsymbol{\beta}\Big)$$

With the `hettype()` option, we reduce the complexity of equation (EXP). In particular, if we ask for `hettype(time)`, we have

$$\begin{aligned}E\left(y_{it}|\mathbf{x}_{it},d_{it},G_{ig},f_s\right) = \exp\Big(&\eta+\sum_{g=q}^{T}G_{ig}\alpha_g+\sum_{s=q}^{T}f_s\gamma_s+\sum_{s=q}^{T}d_{it}f_s\tau_s+\sum_{g=q}^{T}G_{ig}\mathbf{x}_i\boldsymbol{\alpha}_g^{\mathbf{x}}\\&+\sum_{s=q}^{T}f_s\mathbf{x}_i\boldsymbol{\gamma}_s^{\mathbf{x}}+\sum_{s=q}^{T}d_{it}f_s\mathbf{x}_i\boldsymbol{\tau}_s^{\mathbf{x}}+\mathbf{x}_{it}\boldsymbol{\beta}\Big)\end{aligned}$$

Now treatment varies over time but not over cohort. If we use the `hettype(cohort)` option, we have

$$\begin{aligned}E\left(y_{it}|\mathbf{x}_{it},d_{it},G_{ig},f_s\right) = \exp\Big(&\eta+\sum_{g=q}^{T}G_{ig}\alpha_g+\sum_{s=q}^{T}f_s\gamma_s+\sum_{g=q}^{T}d_{it}G_{ig}\tau_g+\sum_{g=q}^{T}G_{ig}\mathbf{x}_i\boldsymbol{\alpha}_g^{\mathbf{x}}\\&+\sum_{s=q}^{T}f_s\mathbf{x}_i\boldsymbol{\gamma}_s^{\mathbf{x}}+\sum_{g=q}^{T}d_{it}G_{ig}\mathbf{x}_i\boldsymbol{\tau}_g^{\mathbf{x}}+\mathbf{x}_{it}\boldsymbol{\beta}\Big)\end{aligned}$$

Now treatment varies over cohort but not over time.

When the `controlgroup(notyet)` option is specified, the $G_{ig}$ indicator excludes the last treated cohort. As discussed in Wooldridge (2025), when every group is eventually treated, we cannot identify the treatment effect for this cohort. It is therefore sensible to use the last treated cohort as a control group. When some of the units in our sample are never treated, we can always identify all cohorts, and the pooled Poisson estimator will always revert to using `controlgroup(never)`.

## Acknowledgments

We thank Fernando Rios-Avila of the London School of Economics and Political Science for helpful conversations and advice and for his contributions in developing heterogeneous treatment-effects software and accompanying material. His community-contributed command `jwdid` implements some of the methods in this entry and a few others.

We thank Jeff Wooldridge of Michigan State University for helpful conversations regarding flexible estimation of nonlinear DID models for panel data.

## References

Wooldridge, J. M. 2023. Simple approaches to nonlinear difference-in-differences with panel data. *Econometrics Journal* 26: C31–C66. https://doi.org/10.1093/ectj/utad016.

———. 2025. Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators. *Empirical Economics* 69: 2545–2587. https://doi.org/10.1007/s00181-025-02807-z.

## Also see

[CAUSAL] **xthdidpoisson postestimation** — Postestimation tools for xthdidpoisson+

[CAUSAL] **DID intro** — Introduction to difference-in-differences estimation

[CAUSAL] **gencohort** — Create a cohort variable

[CAUSAL] **teffects intro** — Introduction to treatment effects for observational data

[CAUSAL] **teffects intro advanced** — Advanced introduction to treatment effects for observational data

[R] **poisson** — Poisson regression

**[U] 20 Estimation and postestimation commands**

Stata, Stata Press, Mata, NetCourse, and NetCourseNow are registered trademarks of StataCorp LLC. Stata and Stata Press are registered trademarks with the World Intellectual Property Organization of the United Nations. StataNow is a trademark of StataCorp LLC. Other brand and product names are registered trademarks or trademarks of their respective companies. Copyright © 1985–2025 StataCorp LLC, College Station, TX, USA. All rights reserved.

For suggested citations, see the FAQ on citing Stata documentation.