5. Event studies

LPO 8852: Regression II

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Introduction

Event studies

Event studies are a class of models that attempt to estimate the effect of an "event" (or treatment) over time on some outcome. This usually involves imputing or modeling a counterfactual time trend. Event studies are often interested in the *dynamic* aspects of treatment effects.

Event studies have a long history, especially in finance, where analysts estimate the effect of a notable event (e.g., new CEO, interest rate announcement) on the market or on an individual stock.

Lecture 4 considered the **interrupted time series** (single unit, before and after) design, which can be considered a type of event study.

Single unit event studies

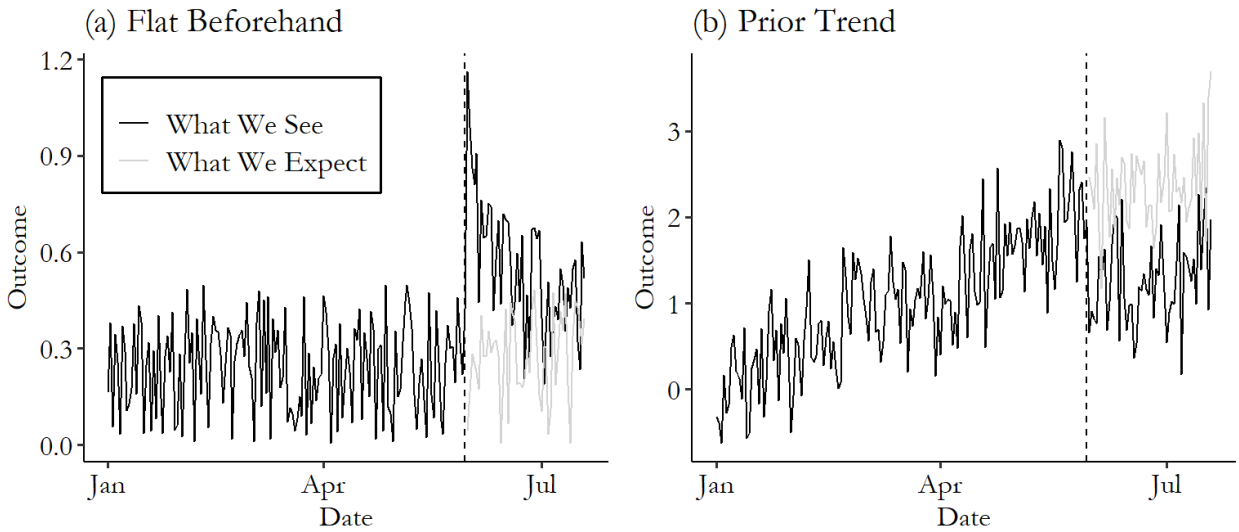
The single unit event study includes one unit observed "before" and "after" some event. To estimate the effect of the event, we need some way to predict the counterfactual.

Our best prediction may be to assume whatever we observed "before" would continue "after" in the absence of intervention. For example, we could fit a linear or nonlinear time trend before the event, or use other informative variables for prediction.

Note: you are unlikely to be estimating many single unit event studies! However, they are useful for building intuition.

Single unit event studies

Extrapolating pre-event trends into the post period:

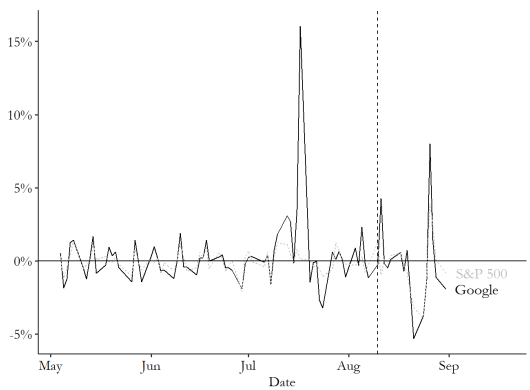


Source: Huntington-Klein chapter 17

Single unit event studies

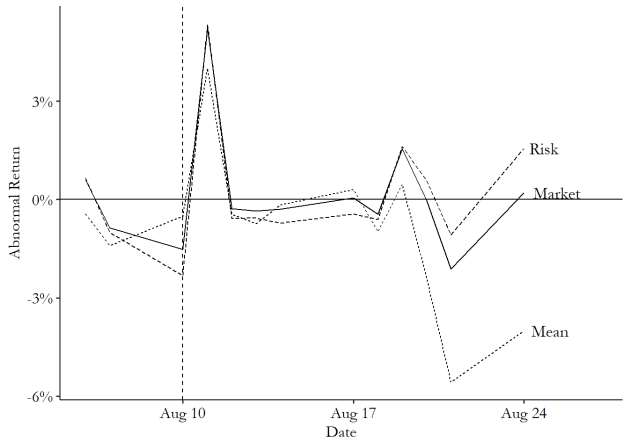
This approach could work well in contexts in which a trend is well established and expected to continue. Example: high-frequency stock price data observed over a relatively short period of time.

H-K: Google announces the creation of Alphabet on August 10, 2015. How did investors value this change? If markets are efficient, prices adjust quickly to new information. Graph: daily price change Google and S&P500



Single unit event studies

In the graph below, H-K plots "abnormal returns" for Google: the difference between the Google daily price change and (1) the *mean* price change in the pre period; (2) the mean price change for the *market* in the pre-period; and (3) the predicted Google price change based on the market price change (estimated in the pre-period; "*risk*").



Source: Huntington-Klein chapter 17

Single unit event studies

In the Google example, the effect was **transitory**. For some outcomes you might expect to see an effect that persists and perhaps changes the time trend thereafter. A simple interrupted time series model for this scenario:

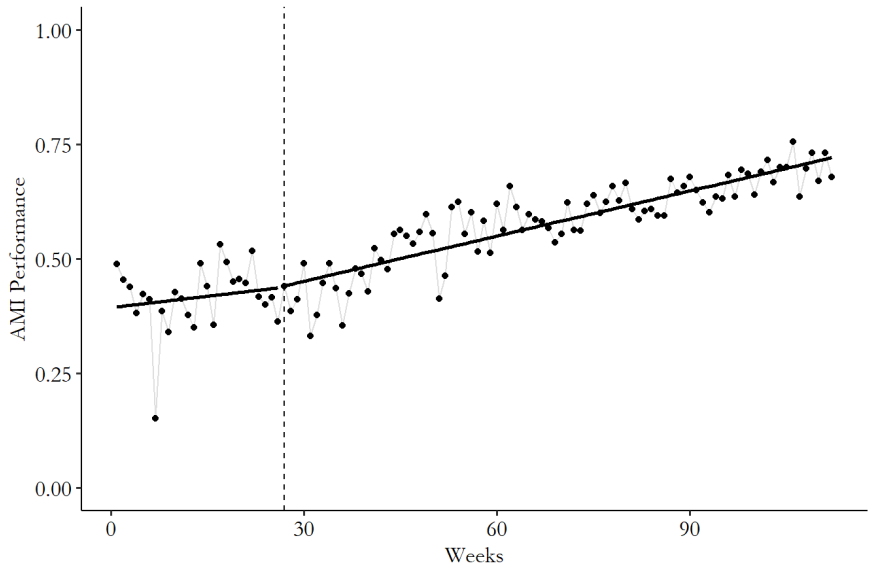
$$Y_t = \beta_0 + \beta_1 t + \beta_2 POST_t + \beta_3 (t \times POST_t) + e_t$$

where t is centered at $t = 0$ when the event occurs. This model assumes a linear time trend. One could use higher-order terms if appropriate.

NOTE: autocorrelation is common with time series data. Use robust standard errors when estimating a model like this.

Single unit event studies

H-K: example estimating the effects of an ambulance health intervention in England in 2010 on heart attack (Taljaard et al 2014).



Source: Huntington-Klein chapter 17

Multiple treated units: common treatment timing

Suppose you have multiple units (i) treated in the same period (and all units are treated). Now with multiple observations per time period, one can estimate separate time fixed effects:

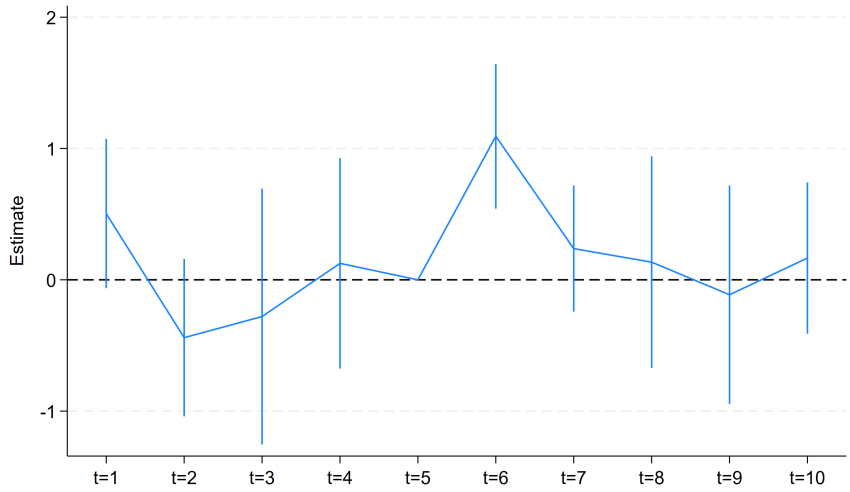
$$Y_{it} = \beta_0 + \gamma_t + e_t$$

where the **last time period before the event** is usually the omitted reference category. The estimated $\hat{\gamma}_t$ trace out the time path of Y relative to the reference period.

H-K: example using simulated data, 10 units and 10 time periods with treatment in $t = 6$. Simulated data do not include a time trend.

Multiple treated units: common treatment timing

Each estimated year effect is relative to $t = 5$. (Treatment is in $t = 6$).



In this example with simulated data, all pre-treatment year effects should be zero (if there is no time trend). Some may yet differ from zero due to sampling variability.

Multiple treated units: common treatment timing

While simple to estimate, there are important limitations to this design:

- There is no untreated comparison group. It is impossible to separate treatment effects from other things changing over time. (Again, see Lecture 4).
- In the real word, events happen at different times.

Event study models

Event time

Define **event time** or **time since event** j as the number of periods since an event occurred for unit i.

$j = 0$ in the period in which treatment occurs

$j = -1$ in the period just before treatment

$j = 1$ in the period just after treatment, etc.

Let m represent the (max) number of periods observed before event

Let n represent the (max) number of periods observed after event

Can refer to E_i as the period in which the event occurs (if any) for unit i. So in time period t, $E_i = t - j$ (or, $j = t - E_i$). Note we are assuming at most one event per unit for now, and the event is "absorbing."

Core features of event study models

$$Y_{it} = \underbrace{\left(\sum_{j \in \{-m,\ldots,0,\ldots n\}} \gamma_j D_{i,t-j} \right)}_{\text{Event study terms}} + \underbrace{\alpha_i + \delta_t}_{\text{Panel fixed effects}} + \beta X_{it} + u_{it}$$

- $D_{i,t-j} = 1$ if the event occurred j periods before the time period t
- α_i is a unit fixed effect, δ_t is a fixed effect for **calendar time**
- Time-varying covariates X_{it} are optional
- Events can occur at higher levels of aggregation (e.g., states)
- The γ_j are the **event study coefficients**
- When estimating, $j = -1$ is usually the omitted reference period

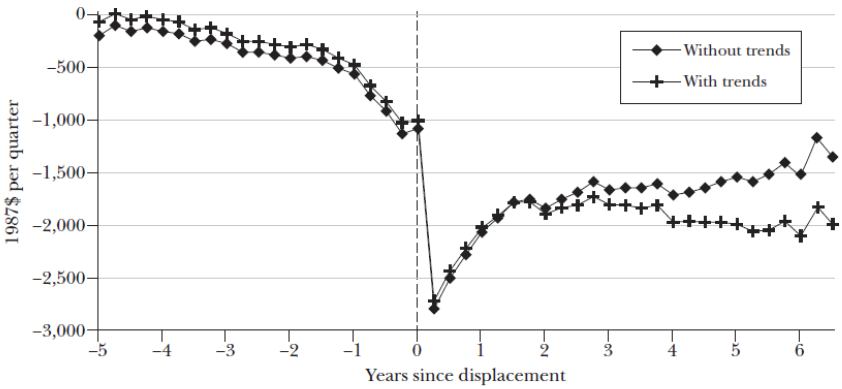
Core features of event study models

- You will notice this is our TWFE difference-in-differences model but with event time dummies for every pre and post period.
- The model can also accommodate "never treated" cases: they have $D_{i,t-j} = 0 \ \forall t$
- The main output—an **event study plot**—is just a plot of the estimated event study coefficients.

Example

An early (1993) example of an event study plot:

Figure 1
An Event Study Example: Loss of Income after Being Displaced from a Job



Source: Jacobson, LaLonde, and Sullivan (1993).
Note: Figure reproduced from Jacobson, LaLonde, and Sullivan (1993). The x-axis is measured in "event time." The y-axis show income for each period relative to a baseline comparison period more than five years prior to the job discplacement.

Source: Jacobson, LaLonde, and Sullivan (1993) reproduced in Miller (2023)

Uses of event study models

Event study models are used for several purposes:

- To estimate **dynamic treatment effects**—when the appropriate assumptions hold.
- To check for differences in pre-trends (e.g., due to anticipation, model mis-specification, omitted time-varying covariates) in a DD design.

Data structure

Miller (2023) characterizes data structures typically used in event studies using two criteria:

1. Are there "never-treated" units?
2. Is there considerable variation in the treatment date across units?

Table 1
Data Structures for Event Study Estimation

	Only Ever-Treated Units	*There are Never-Treated Units*
Common Event Date	N/A	DiD-type
Varying Event Date	Timing-based	Hybrid

Note: Author's proposed labels for event study data structures, based on whether the analysis data sample uses never treated units or not, and on whether treated units have a common event date or varying event dates. "DiD-type" = "Difference in Difference type."

You should be able to answer "yes" to one or both of these questions.

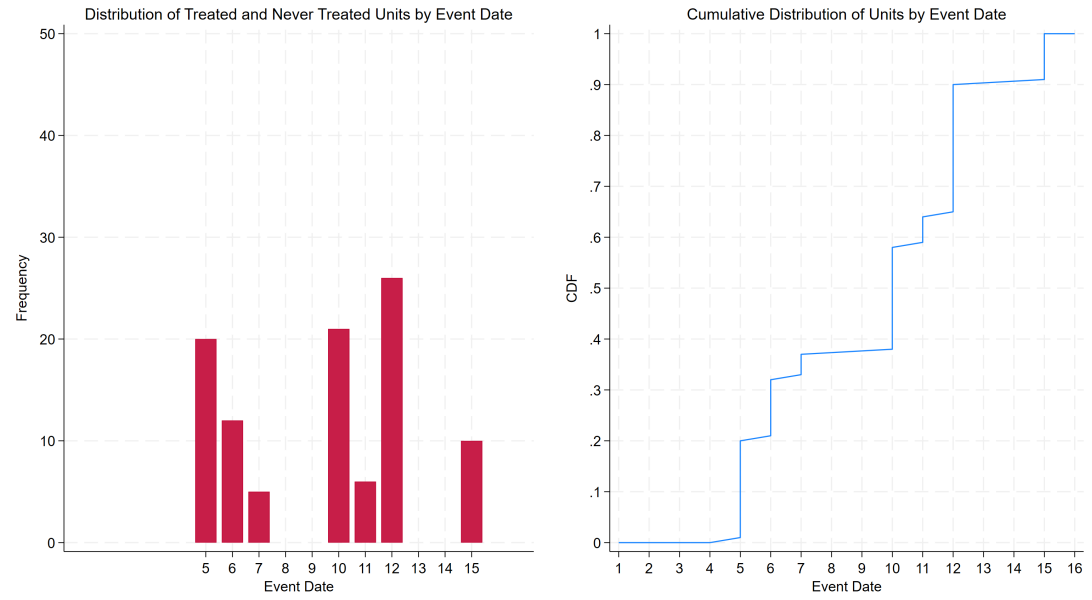
Data structure

- Top left: single group before and after; hard to identify treatment effects.
- "DiD type": treated and untreated units before and after.
- "Timing based": only treated units but treatment times vary. Assume timing is as good as random.
- "Hybrid": comparisons to untreated and treated earlier/later.

It is important to be clear with the reader about which data structure you have, and the distribution of observations across event times. See following examples of graphical ways to communicate this.

Data structure: event timing

All units are treated but at varying times:

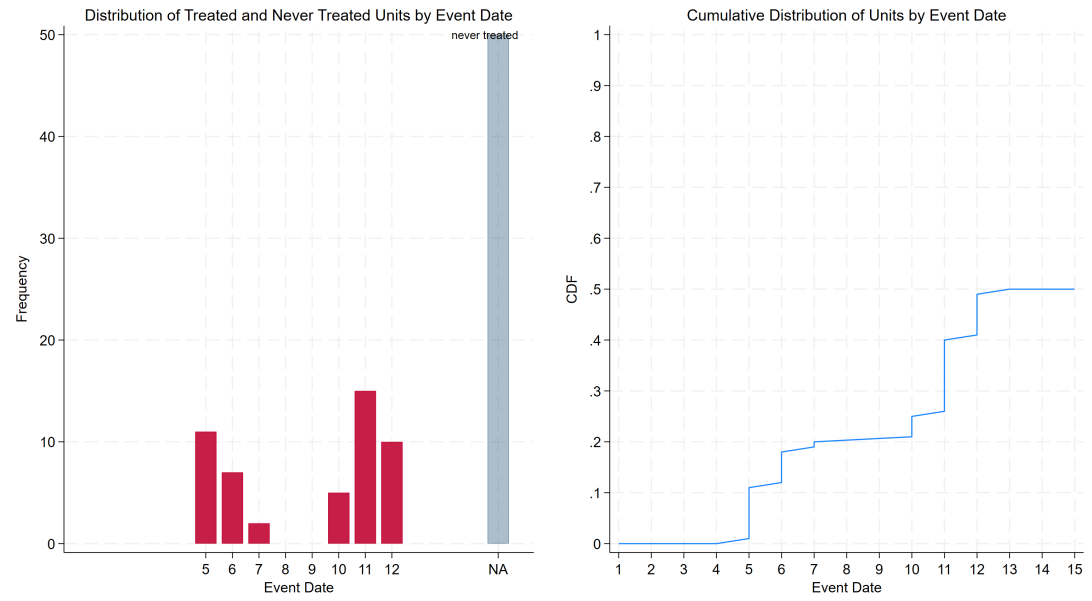


Probability and cumulative distribution functions

Source: Miller (2023) appendix

Data structure: event timing

Data has "never treated" units:



Probability and cumulative distribution functions

Source: Miller (2023) appendix

Estimation

Estimation and interpretation: example

The event study model above can be estimated using OLS and `regress` in Stata.

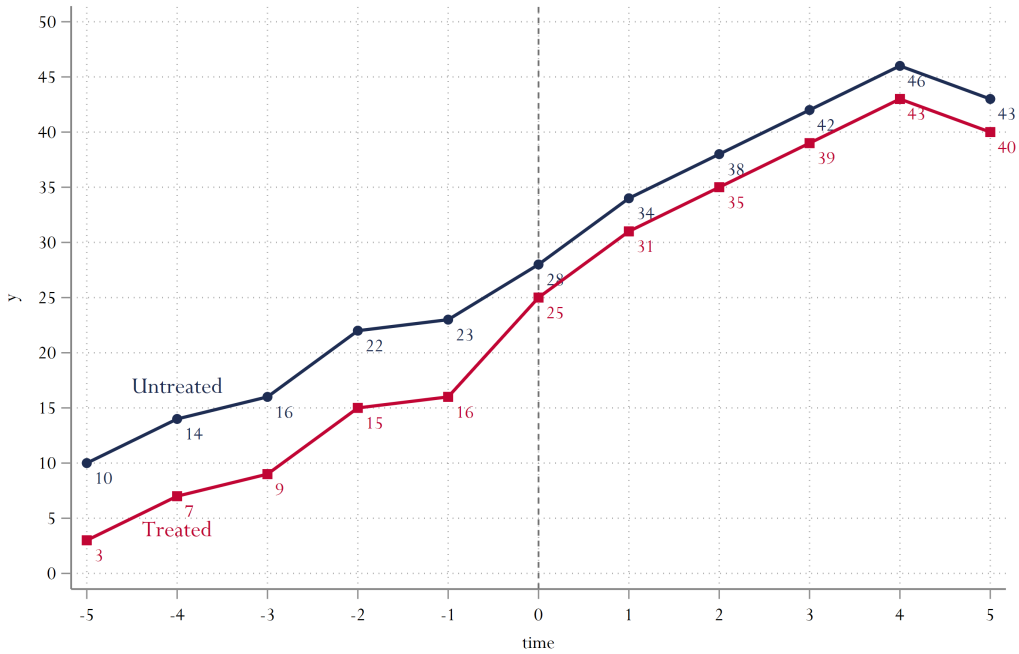
Example: Stylized data with multiple units, a common treatment period, and a "never treated" group.

```
reg y2 i.treated##ib4.etime2
```

This is a full factorial of treatment group status and time period—includes main effects for *treated* and each year, and their interaction. You will need to specify the omitted time period. Here the omitted reference group is time period 4 (the year before treatment in this case).

Estimation and interpretation: example

Stylized example: plot the mean observed Y in each time period for the treated and untreated:



Estimation and interpretation: example

```
. reg y2 i.treated##ib4.etime2
```

Source	SS	df	MS	Number of obs	=	1,100
				F(21, 1078)	=	193.37
Model	182849.286	21	8707.10886	Prob > F	=	0.0000
Residual	48540.4525	1,078	45.0282491	R-squared	=	0.7902
				Adj R-squared	=	0.7861
Total	231389.739	1,099	210.545713	Root MSE	=	6.7103

y2	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
1.treated	-8.379426	1.342062	-6.24	0.000	-11.01278	-5.746076
etime2						
-5	-13.99077	1.342062	-10.42	0.000	-16.62412	-11.35742
-4	-9.457968	1.342062	-7.05	0.000	-12.09132	-6.824618
-3	-5.494279	1.342062	-4.09	0.000	-8.127629	-2.86093
-2	1.748657	1.342062	1.30	0.193	-.8846928	4.382006
0	3.477879	1.342062	2.59	0.010	.8445296	6.111229
1	7.835866	1.342062	5.84	0.000	5.202516	10.46922
2	16.10816	1.342062	12.00	0.000	13.47481	18.74151
3	16.83639	1.342062	12.55	0.000	14.20304	19.46974
4	22.24522	1.342062	16.58	0.000	19.61187	24.87857
5	19.24763	1.342062	14.34	0.000	16.61428	21.88097
treated#etime2						
1#-5	2.958434	1.897962	1.56	0.119	-.7656849	6.682552
1#-4	1.876838	1.897962	0.99	0.323	-1.84728	5.600957
1#-3	.0605446	1.897962	0.03	0.975	-3.663574	3.784663
1#-2	-1.621474	1.897962	-0.85	0.393	-5.345592	2.102645
1#0	7.718263	1.897962	4.07	0.000	3.994145	11.44238
1#1	7.082635	1.897962	3.73	0.000	3.358517	10.80675
1#2	4.351253	1.897962	2.29	0.022	.6271342	8.075371
1#3	6.906317	1.897962	3.64	0.000	3.182199	10.63044
1#4	6.213328	1.897962	3.27	0.001	2.489209	9.937447
1#5	5.132189	1.897962	2.70	0.007	1.408071	8.856308
_cons	23.43028	.948981	24.69	0.000	21.56822	25.29234

Estimation and interpretation: example

Interpreting the coefficients:

- Constant term: mean outcome for untreated in the base period.
- Coefficient on "treated": *difference* in mean outcome between the treated and untreated in the base period.
- Coefficients on event time (-5 to +5): difference between time period k and the base period, for the *untreated* group.
- Coefficients on event time $\times$ treated interaction: the difference in mean outcomes between the treated and untreated groups in period k relative to their prevailing difference in the base year.

With parallel trends, would expect the coefficients on the pre-treatment interactions to be zero.

Estimation using `eventdd`

The user-written Stata package `eventdd` is a flexible solution that automatically generates the needed variables, estimates the regression, and produces an event study plot. Example syntax:

`eventdd` *`y x1 x2 i.group`*`, timevar(`*`eventtime`*`)`

This syntax estimates an OLS model with the *group* main effect included in the covariates (see next slide for panel version). The key variable here is *eventtime* (a variable name you provide), defined as the **relative time** to treatment. 0 corresponds to the first year of treatment, -1 refers to the first lead, and so on. This variable should be **missing for groups that are never treated**. See Clarke and Schythe (2020).

Estimation using eventdd

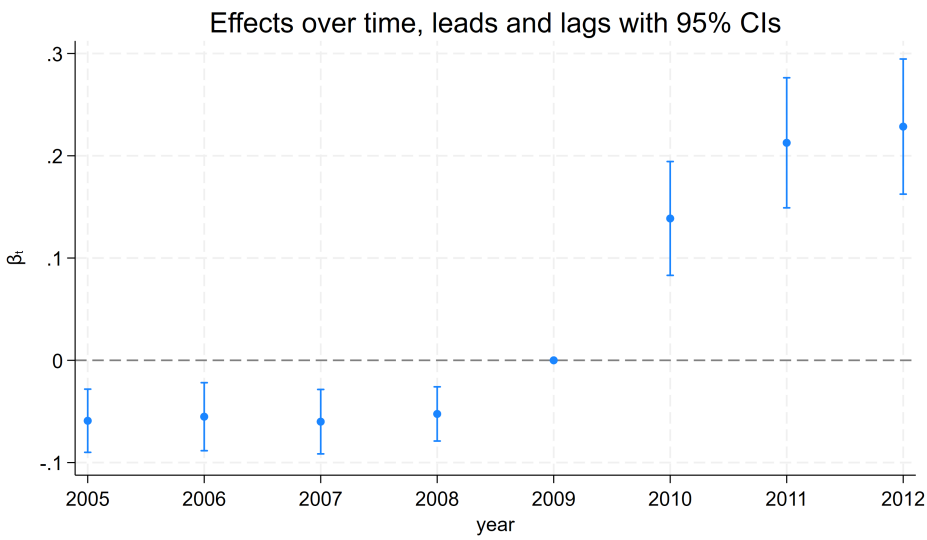
With lots of groups (or panel data) you can have eventdd estimate a fixed effects model specification:

`eventdd` *y x1 x2*, `timevar(`*timetoevent*`) method(fe, absorb(group))`

Here the command uses `xtreg` where the variable *state* is used as the fixed effect.

Event study plots using grangerplot

The post-estimation command `estat grangerplot` also produces event study plots, following `didregress` or `xtdidregress`



Event study example: Miller et al (2021)

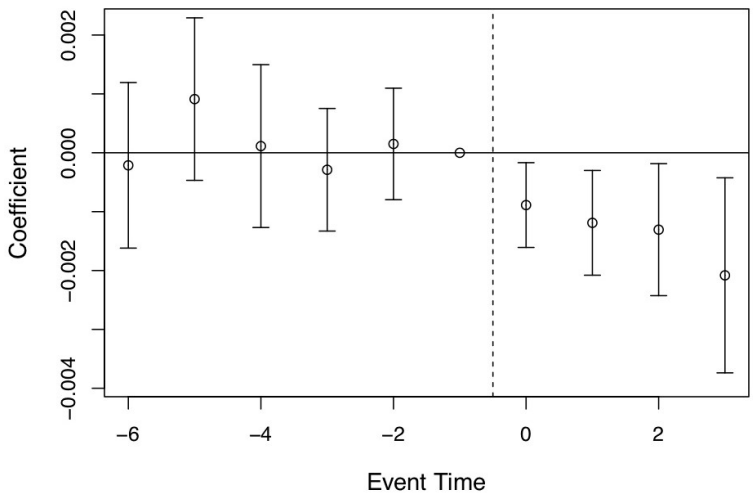
The following figures are from Miller et al. (QJE 2021), via the *Mixtape*. The authors estimate the impact of state expansion of Medicaid under ACA on the annual mortality rates of older persons under 65 in the U.S.

A causal interpretation of DD assumes changes over time in states that did *not* expand Medicaid provide the counterfactual for those that did.

They find a 0.13 percentage-point decline in annual mortality, a 9.3% reduction over the sample mean, as a result of Medicaid expansion.

Event study example: Miller et al (2021)

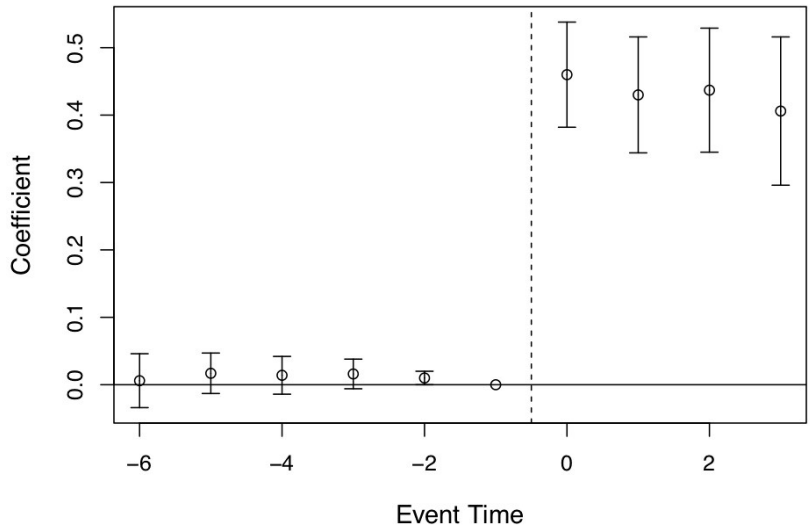
Plotted points are event study coefficients, shown with 95% confidence intervals. (Time zero is the first year of expansion). Outcome: mortality rate



There is no evidence these states' mortality rates were on different trajectories prior to Medicaid expansion.

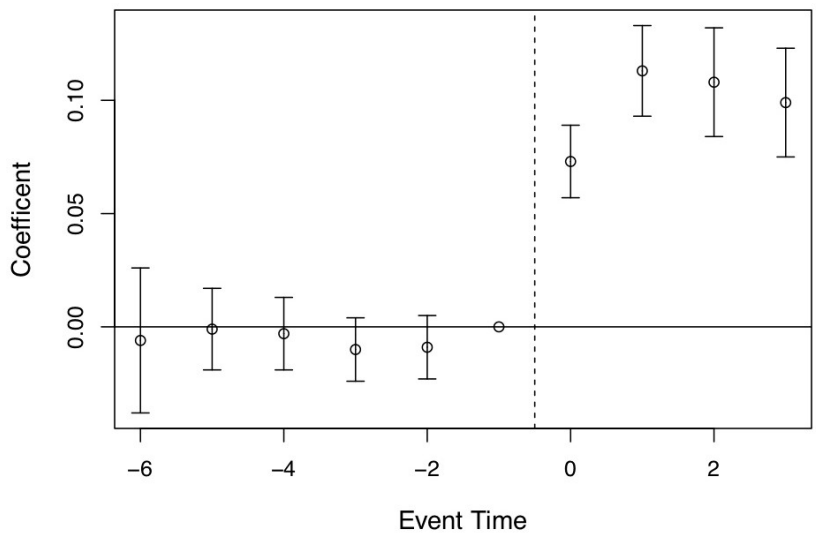
Event study example: Miller et al (2021)

The authors first look for a "first stage": did the expansion of Medicaid actually increase rates of eligibility for Medicaid? Did it increase Medicaid coverage? Did it lower the uninsured rate? Here: **eligibility**



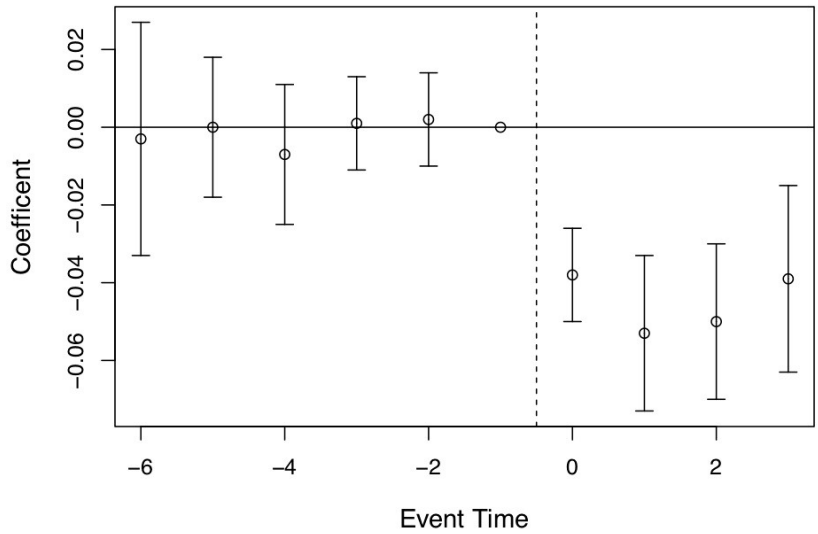
Event study example: Miller et al (2021)

Here: Medicaid **coverage rates**



Event study example: Miller et al (2021)

Here: **uninsured rates**



Taken together, these graphs are compelling: Medicaid expansion increased eligibility and coverage, and reduced the uninsured. One would hope to see these first stage effects before expecting an effect on health outcomes.

Event study issues and analytic decisions

Event study issues and analytic decisions

Miller (2023) identifies some important issues and analytic decisions that arise when estimating event studies:

- "Multicollinearities abound," forcing some restrictions on parameters
- Alternatives to "one period before treatment" as base period
- Control units to include/exclude (or use of re-weighting to balance covariates)
- Choice of event window
- Endpoint considerations
- Pooling event times for statistical power

"Multicollinearities abound"

"Multicollinearities abound" in event study models.

- Of course, cannot include dummies for every group and every calendar time period; one (each) must be left out as a reference group.
- However, event-time is also linked to calendar time and event date: $j = t - E_i$. Groups are defined by their common event date, so knowing j and t identifies your group. This is more problematic in "timing based" structures where all are treated at some point.
- Stata will automatically drop coefficients, but these may not be the ones you want. Note that estimated treatment effects can be sensitive to the choice of reference groups.

"Multicollinearities abound"

Some advice:

- Be attentive to omitted groups/time periods.
- Pooling data by creating "end-cap" variables can help (e.g., "m or more" periods before treatment)
- The appendix to Miller (2023) provide some examples of how you can enforce control over model restrictions. `eventdd` also provides flexibility.

Alternatives to "one period before treatment" as base

When using "one period before treatment" as the reference period—which is the standard approach—a lot of importance is placed on that one period.

- Miller (2023) makes the case for using a larger "pre-event" window to improve precision. In this case, constrain coefficients in a pre-event window to average zero.
- How long of a windows? Consider what you might find acceptable for a DD model.
- Note: making this change affects the event study plot (shifts it up or down), with implications for how to use the results to inspect pre-trends.

Alternatives to "one period before treatment" as base

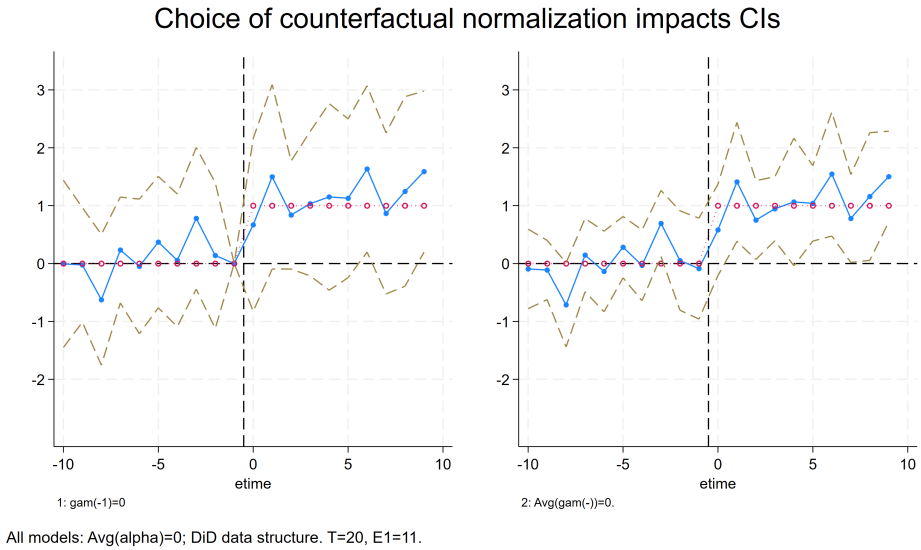


Figure on the right: constraints coefficient on time periods -1 and -2 to equal zero. Note improvement in precision.

Endpoint considerations

In practice, not all event studies have dummies variables for every event time.

- Analysts sometimes use "end-cap" variables for pre- or post- periods (e.g., "m or more" periods before treatment, "n or more" periods after treatment).
- Benefits: extreme time periods often have thinner data, and this improves precision.
- Drawbacks: can be misleading if there are trends in the counterfactual or in treatment effects.
- Graphing: be sure endcaps are clearly indicated, since they have a different interpretation.

There are other things one can do to improve precision, like pooling adjacent periods, etc. See Miller (2023).