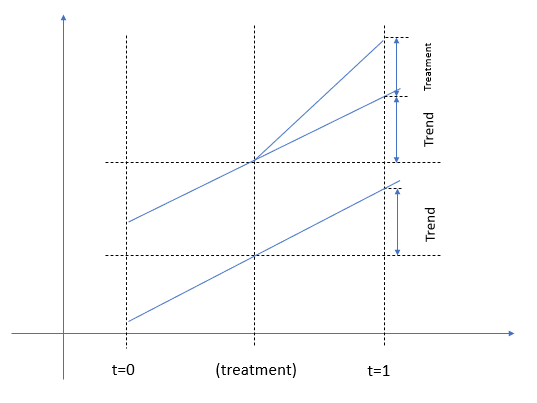
## Day 4: DID Analysis and Propensity Score Model

1. **DID Basic Idea**



Two time periods (), two groups (treatment group and control group).

Parallel trend assumption: the outcomes of both groups would have followed the same trend over time if treatment were not in place.

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webuse hospdd

Several hospitals are using a new procedure for registration, we would like to see if the new procedure affects patients’ outcomes, measured by *satis*.

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

-----*The model specifications should be enclosed in parentheses*

estat trendplots

estat ptrend

-----*Cannot reject null hypothesis, therefore parallel trend is satisfied*

estat granger

-----*‘Placebo’ test, cannot reject null hypothesis, therefore the effects exists*

*OR*

reghdfe satis procedure, absorb(hospital month)

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1. **Two-way fixed static DID model**

Beck et.al (2010), Big bad banks? The winners and losers from bank deregulation in the United States. *The Journal of Finance*, 65(5): 1637-1667.

is a dummy variable of our interest, in equals one in the years after unit *s* is treated.

Fixed effects: and

1. **Event study DID model**

Model from my own paper:

A black and white math symbols

Description automatically generated with medium confidence

With multiple treatment timing, we would like to know how treatment effects vary across time with an event study model.

-----*The canonical DID model might be biased in multiple time treatment settings. Event study model might also be biased but that’s another story.*

The basic idea is to compare the outcomes with base time ( here).

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Cheng, C., & Hoekstra, M. (2013). Does Strengthening Self-Defense Law Deter Crime or Escalate Violence? Evidence from Expansions to Castle Doctrine. The Journal of Human Resources, 48(3), 821–853. <http://www.jstor.org/stable/23799103>

*Between 2000 and 2010, twenty-one states explicitly expanded the castle-doctrine statute by extending the places outside the home where lethal force could be legally used.*

Crimes were converted into rates, or “offenses per 100,000 population.” (Variable *homicide*)

Castle-Doctrine Law become effective (Variable *effyear*)

use https://github.com/scunning1975/mixtape/raw/master/castle.dta, clear

global demo blackm\_15\_24 whitem\_15\_24 blackm\_25\_44 whitem\_25\_44

global spending l\_exp\_subsidy l\_exp\_pubwelfare

global xvar l\_police unemployrt poverty l\_income l\_prisoner l\_lagprisoner $demo $spending

---*Globalize our variables*

gen DID=1 if year>=effyear

replace DID=0 if missing(DID)

---*Create DID variable for Two-way fixed static model*

reghdfe l\_homicide DID i.year $xvar [aweight=popwt], absorb(sid)

reghdfe l\_homicide DID i.year $xvar, absorb(sid)

xtreg l\_homicide DID i.year $xvar ,fe

----*Static regression*

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forvalues i=1/5{

gen post`i'=1 if rel\_year==`i'

replace post`i'=0 if missing(post`i')

}

forvalues i=1/7{

gen pre`i'=1 if rel\_year==-`i'

replace pre`i'=0 if missing(pre`i')

}

gen current=1 if rel\_year==0

replace current=0 if missing(current)

-----*Create Event Study DID variables*

replace post5=1 if rel\_year>5 &!missing(rel\_year)

replace pre7=1 if rel\_year<-7 &!missing(rel\_year)

reghdfe l\_homicide pre7 pre6 pre5 pre4 pre3 pre2 current post1 post2 post3 post4 post5 $xvar, absorb(year sid)

-----*As baseline, pre1 is not included here*

coefplot, baselevels keep(pre7 pre6 pre5 pre4 pre3 pre2 current post1 post2 post3 post4 post5) vertical coeflabels(pre7="-7" pre6="-6" pre5 = "-5" pre4 = "-4" pre3 = "-3" pre2 = "-2" current = "0" post1 = "1" post2 = "2" post3 = "3" post4="4" post5="5") yline(0) ylabel(-0.5(0.1)0.6) xline(6.5, lwidth(vthin) lpattern(dash) lcolor(teal)) ylabel(,labsize(\*0.75)) xlabel(,labsize(\*0.75)) ytitle("Dynamic Effect", size(small)) xtitle("Rel\_year", size(small)) addplot(line @b @at) ciopts(lpattern(dash) recast(rcap) msize(medium)) msymbol(circle\_hollow) scheme(s1mono)

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did2s l\_homicide, first\_stage($xvar i.sid i.year) second\_stage(i.DID) treatment(DID) cluster(sid)

---- *did2s*

did2s l\_homicide, first\_stage($xvar i.sid i.year) second\_stage(pre7 pre6 pre5 pre4 pre3 pre2 current post\*) treatment(DID) cluster(sid)

---- *did2s Event Study*

1. **Propensity Score Model Basic Idea**

Selection bias in some analysis.

---The policy treatment is not randomly assigned; some units are favored over others.

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Step 1: select covariates for estimating propensity scores.

---An easier option is to use your control variables, depending on your research context, other variables are preferred.

Step 2: estimate propensity scores with a logit or probit model.

---logit model is preferred. The dependent variable is a dummy variable indicating treatment status.

Step 3: match with the given propensity scores and calculate treatment effect.

---kth nearest matching with a given caliper.

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1. **STATA**

ssc install psmatch2

----*the propensity score matching package in STATA*

bysort DID: summarize l\_homicide $xvar

----*summarize our variables by treatment, check if there is a difference between different groups.*

psmatch2 DID $xvar, outcome(l\_homicide) logit neighbor(2) ties common ate caliper(0.05)

----*DID is the treatment indicator we had earlier*

----*followed by outcome is our dependent variable*

----*we use logit model*

----*ties indicate if multiple units from control group share the same propensity score, we took their average.*

----*ate reports both average treatment effect, average treatment effect on the treated and average treatment effect on the untreated*.

----*caliper is set to 0.05. for someone from treatment group, if no one from the control group has the propensity score within the calipered range, it will be dropped from analysis.*

pstest, both graph saving(balancing\_assumption, replace)

psgraph, saving(common\_support, replace)

----*psmatch2 generates a list of new variables:*

*pscore is the propensity score calculated*

*treated is treatment status, same as our DID*

*support indicates whether it was matched*

*weight: for control group, it is calculated based on how many times it was matched. weight = k/m, where k is how many times the certain unit is matched, and m is how many control group units each treatment group matches.*

*id: id assigned to each unit*

*n1/n2: whom this unit is matched with*

*nn: how many units from control group a unit in the treatment group is matched with*

*pdif: the absolute difference between propensity scores of matched pairs.*

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reghdfe l\_homicide DID $xvar if \_weight != . , noabsorb

est store m1

reghdfe l\_homicide DID $xvar if \_support == 1, noabsorb

est store m2

gen weight = \_weight \* 2

replace weight = 1 if treated == 1 & \_weight != .

reghdfe l\_homicide DID $xvar [fweight = weight], noabsorb

est store m3

esttab m1 m2 m3