10. Difference in Differences

ECON8011 Microeconometrics

Burcu Duzgun Oncel *

*Marmara University Department of Economics

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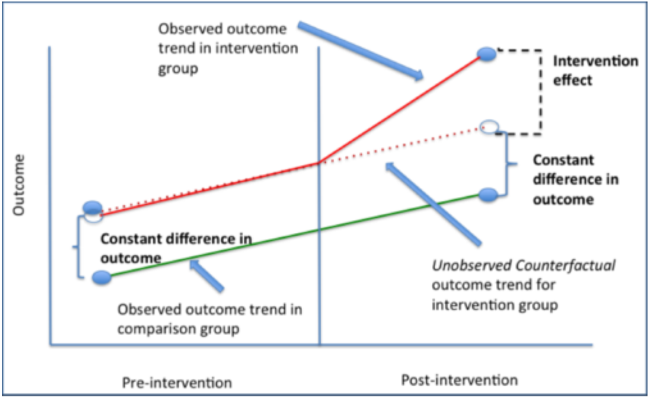
Description

- DID is a quasi-experimental design that makes use of longitudinal data from treatment and control groups to obtain an appropriate counterfactual to estimate a causal effect.

- DID is typically used to estimate the effect of a specific intervention or treatment (such as a passage of law, enactment of policy, or large-scale program implementation) by comparing the changes in outcomes over time between a population that is enrolled in a program (the intervention group) and a population that is not (the control group).


Observed outcome trend in intervention group
Intervention effect
Constant difference in outcome
Outcome
Constant difference in outcome
Unobserved Counterfactual outcome trend for intervention group
Observed outcome trend in comparison group
Pre-intervention
Post-intervention

- DID is used in observational settings where exchangeability cannot be assumed between the treatment and control groups.
- Difference-in-difference is a useful technique to use when randomization on the individual level is not possible.
- DID requires data from pre-/post-intervention, such as cohort or panel data (individual level data over time) or repeated cross-sectional data (individual or group level).
- The approach removes biases in post-intervention period comparisons between the treatment and control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends due to other causes of the outcome.

History

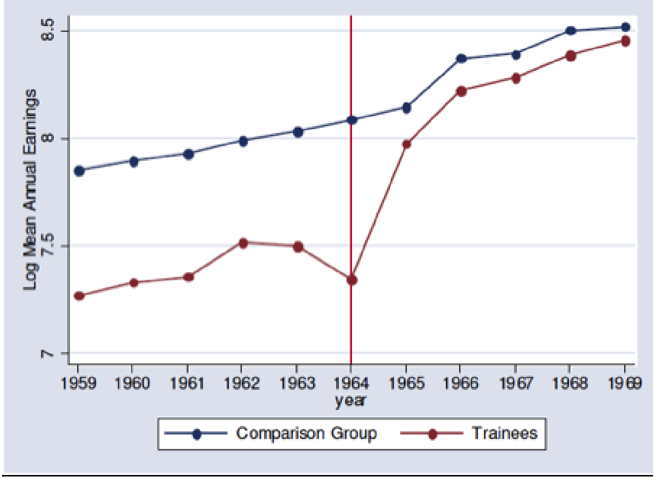
- DID idea pioneered by John Snow (1855) studying Cholera.
- Since mid 1990s heavily used in economics.
- A classical example: Card and Krueger (AER 1994).
- 2018 - 2020: explosion of work on the DID designs.

Assumptions

- Intervention unrelated to outcome at baseline (allocation of intervention was not determined by outcome).
- Treatment/intervention and control groups have Parallel Trends in outcome.
- Composition of intervention and comparison groups is stable for repeated cross-sectional design.
- No spillover effects.

Parallel Trends Assumptions

- It requires that in the absence of treatment, the difference between the "treatment" and "control" group is constant over time.
- Although there is no statistical test for this assumption, visual inspection is useful when you have observations over many time points.
- Violation of parallel trend assumption will lead to biased estimation of the causal effect.


8.5
8
7.5
7
Log Mean Annual Earnings
1959
1960
1961
1962
1963
1964
1965
1966
1967
1968
1969
year
Comparison Group
Trainees

Strengths

- Intuitive interpretation.
- Can obtain causal effect using observational data if assumptions are met.
- Comparison groups can start at different levels of the outcome. (DID focuses on changerather than absolute levels).
- Accounts for change/change due to factors other than intervention.

Limitations

- Requires baseline data & a non-intervention group.
- Cannot use if intervention allocation determined by baseline outcome.
- Cannot use if comparison groups have different outcome trend (Abadie 2005 has proposed solution).
- Cannot use if composition of groups pre/post change are not stable.

Canonical (2x2) DID Estimator

- 2x2:two groups (T,C)& two periods (1,2)
- Calculation via sample means

	Treatment group	Control group
Period 1	$\overline{Y^{T,1}}$	$\overline{Y^{C,1}}$
Period 2	$\overline{Y^{T,2}}$	$\overline{Y^{C,2}}$

- DID Estimator: $(\overline{Y^{T,2}} - \overline{Y^{C,2}}) - (\overline{Y^{T,1}} - \overline{Y^{C,1}})$
- Relies on exogenous variation that alters treatment status.
- DID estimate gives the ATT.

2x2 DID Estimator in a Regression Framework

- Binary indicator for treated group: T_i
- Binary indicator for the second time period: P_t
- $T_i x Post_t (= D_{it})$
- Full saturate model (with four values):

  $$Y_{it} = \alpha + \gamma T_i + \lambda Post_t + \delta(T_i x Post_t) + \epsilon_{it}$$

  - *alpha*: C in period 1
  - γ: difference between C and T in period 1
  - λ: aggregate difference between period 1 and period 2
  - δ: 2x2 DID estimator (ATT)

Demonstration

- A health provider wants 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 in some of their hospitals.
- The health provider will use DID regression to analyze the effect of the new admissions procedure on the hospitals that participated in the program.
- The outcome of interest is patient satisfaction, satis, and the treatment variable is procedure.
- We can fit this model using didregress.

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

- The first set of parentheses is used to specify the outcome of interest followed by the covariates in the model. In this case, there are no covariates.
- The second set of parentheses is used to specify the binary variable that indicates the treated observations, procedure.
- The group() and time() options are used to construct group and time fixed effects that are included in the model.
- The variable specified in group() defines the level of clustering for the default cluster-robust standard errors. For this example, we cluster at the hospital level.

```
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)

                          Robust
       stais   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.
```

- The first table gives information about the control and treatment groups and about treatment timing.
- The first section tells us that 28 hospitals continued to use the old procedure and 18 hospitals switched to the new one.
- The second section tells us that all hospitals that implemented the new procedure did so in the fourth time period.
- If some hospitals had adopted the policy later, the minimum and maximum time of the first treatment would differ.
- The second table gives the estimated ATT, 0.85 (95% CI [0.78,0.91]). Treatment hospitals had a 0.85-point increase in patient satisfaction relative to if they hadn't implemented the new procedure.

- One of the assumptions this model makes is that the trajectories of satis are parallel for the control and treatment groups prior to implementation of the new procedure.
- A visual check of these trajectories can be obtained by plotting the means of the outcome over time for both groups or by visualizing the results of the linear-trends model.

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. estat trendplots
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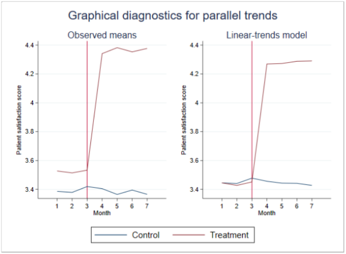

- Prior to the policy implementation, control and treatment hospitals followed a parallel path.

```
. estat ptrends

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

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

- We do not have sufficient evidence to reject the null hypothesis of parallel trends. This test and the graphical analysis support the parallel-trends assumption.

Card and Krueger (1994)

- Card and Krueger (1994): use an increase in the minimum wage in NJ (in 1992) using a standard diff-in-diff methodology.
- In February 1992 NJ increased the state minimum wage from $4.25 to $5.05. Pennsylvania's minimum wage stayed at $4.25.
- They surveyed about 400 fast food stores both in NJ and in PA both before and after the minimum wage increase in NJ.
- Assume that employment is only driven by state-specific and time-specific trends only, in the absence of the policy (parallel trend assumption).
- Then

  $$Y_{ist} = \gamma_s + \lambda_t + \delta Dst + \epsilon ist$$

  where D_{st} s a dummy for high-minimum wage states and periods.

- The difference-in-differences strategy amounts to comparing the change in employment in NJ to the change in employment in PA.
- The difference-in-differences in the population are:

  $$(E[Y_{ist}|s = NJ, t = Nov] - E[Y_{ist|s=NJ,t=Feb}])$$
  $$-(E[Y_{ist}|s = PA, t = Nov] - E[Y_{ist}|s = PA, t = Feb])$$

  which is equal to δ.

Main Estimates

	Stores by state		
Variable	PA (i)	NJ (ii)	Difference, NJ − PA (iii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	−2.89 (1.44)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	−0.14 (1.07)
3. Change in mean FTE employment	−2.16 (1.25)	0.59 (0.54)	$\boxed{2.76 \ (1.36)}$

DID in a Regression Framework

- Regression model in Card and Krueger (1994).

  $$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s x d_t) + \epsilon_{ist}$$

- This equation can take up the following values:
  - PA Pre: α
  - PA Post: $\alpha + \lambda$
  - NJ Pre: $\alpha + \gamma$
  - NJ Post: $\alpha + \gamma + \lambda + \delta$

- So that δ is our DID estimate:

  $$(NJPost - NJPre) - (PAPost - PAPre) = \delta$$

Graphically

$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s \times d_t) + \epsilon_{ist}$$