Chapter 13: Pooling Cross Sections across Time

Introductory Econometrics: A Modern Approach

Outline

13.1 Pooling Independent Cross Sections across Time

- Time trends

13.2 Policy Analysis with Pooled Cross Sections

- Difference in Differences Estimation
- Parallel trend assumption

13.3 Two-period panel data analysis

- Differentiating

13.1 Policy analysis with pooled cross sections

Two or more independently sampled cross sections can be used to evaluate the impact of a certain event or policy change.

Example: Effect of new garbage incinerator's location on housing prices.

Examine the effect of the location of a house on its price before and after the garbage incinerator was built:

$$\widehat{rprice} = \underset{(3,093.0)}{101,307.5} - \underset{(5,827.71)}{30,688.27}\ nearinc$$

$n = 142, R^2 = .165$

After incinerator was built

$$\widehat{rprice} = \underset{(2,653.79)}{82,517.23} - \underset{(4,744.59)}{18,824.37}\ nearinc$$

$n = 179, R^2 = .082$

Before incinerator was built

Policy analysis with pooled cross sections

Example: Garbage incinerator and housing prices

- It would be wrong to conclude from the regression after the incinerator is there that being near the incinerator depresses prices so strongly.
- One has to compare with the situation before the incinerator was built:

$$\hat{\delta}_1 = -30,688.27 - (-18,824.37) = -11,863.9$$

Incinerator depresses prices, but location was one with lower prices anyway!

In the given case, this is equivalent to:

$$\hat{\delta}_1 = \left(\overline{\text{rprice}}_{1,nr} - \overline{\text{rprice}}_{1,fr}\right) - \left(\overline{\text{rprice}}_{0,nr} - \overline{rprice}_{0,fr}\right)$$

This is called the differences-in-differences estimator (DiD)

Difference-in-differences in a regression framework

$$rprice = \beta_0 + \delta_0 after + \beta_1 nearinc + \delta_1 after * nearinc + u$$

- In this way standard errors for the DiD-effect can be obtained.
- δ_1: **differential effect of being in the location AND after the incinerator was built**
- If houses sold before and after the incinerator was built were systematically different, further explanatory variables should be included.
- This will also reduce the error variance and thus standard errors.
- Before/After comparisons in “natural experiments”
- DiD can be used to evaluate policy changes or other exogenous events.

Policy evaluation using difference-in-differences

$$y = \beta_0 + \delta_0 after + \beta_1 treated + \delta_1 after * treated + other factors$$

Compare outcomes of the two groups before and after the policy change:

$$\hat{\delta}_1 = (\bar{y}_{1,T} - \bar{y}_{1,C}) - (\bar{y}_{0,T} - \bar{y}_{0,C})$$

- Compare the difference in outcomes of the units that are affected by the policy change (= treatment group) and those who are not affected (= control group) before and after the policy was enacted.
- For example, the level of unemployment benefits is cut but only for group A (= treatment group).
    - Group A normally has longer unemployment duration than group B (= control group).
    - If the difference in unemployment duration between group A and group B becomes smaller after the reform, reducing unemployment benefits reduces unemployment duration for those affected.
    - **Caution: Difference-in-differences only works if the difference in outcomes between the two groups is not changed by other factors than the policy change (e.g. there must be no differential trends).**

13.3 Two-period panel data analysis

Example: Effect of unemployment on city crime rate

- Will it be possible to estimate the causal effect of unemployment on crime? Assume that no other explanatory variables are available.
    - Yes, if cities are observed for at least two periods and other factors affecting crime stay approximately constant over those periods:

$$crmrte_{it} = \beta_0 + \delta_0 d87_t + \beta_1 unem_{it} + a_i + u_{it}, \quad t = 1982, 1987$$

Time dummy for the second period

Unobserved time-constant factors (= fixed effect)

Other unobserved factors (= idiosyncratic error)

Example: Effect of unemployment on city crime rate

- Crime rate and unemployment rate in 1987 and 1982.
- a_i are city characteristics which do not change over time (time-invariant characteristics)

$$\begin{aligned}
\text{crmrte}_{\,i1987} &= \beta_0 + \delta_0 \cdot 1 + \beta_1 \text{ unem}_{\,i1987} + a_i + u_{i1987} \\
\text{crmrte}_{\,i1982} &= \beta_0 + \delta_0 \cdot 0 + \beta_1 \text{ unem}_{\,i1982} + a_i + u_{i1982} \\
\text{Subtract:} \Rightarrow \;\; \text{drmrte} &= \delta_0 + \beta_1 \Delta \text{ unem}_{\,i} + \Delta u_i \longleftarrow \;\; \text{Fixed effect drops out}
\end{aligned}$$

Estimate differenced equation by OLS:

$$\Delta \widehat{crmrte} = \underset{(4.70)}{15.40} + \underset{(.88)}{2.22} \, \Delta unem$$

+ 1 percentage point unemployment rate leads to 2.22 more crimes per 1,000 people

$$n = 46, R^2 = .127$$

Secular increase in crime

Discussion of first-differenced panel estimator

- Further explanatory variables may be included in original equation.
- Note that there may be arbitrary correlation between the unobserved time-invariant characteristics and the included explanatory variables.
    - OLS in the original equation would therefore be inconsistent.
- The first-differenced panel estimator is thus a way to consistently estimate causal effects in the presence of time-invariant endogeneity.
- First-differenced estimates will be imprecise if explanatory variables vary only little over time (no estimate possible if time-invariant).

Another interpretation of the difference-in-differences estimator

We can re-write the DiD estimator as:

$$\hat{\delta}_1 = (\bar{y}_{1,T} - \bar{y}_{0,T}) - (\bar{y}_{1,C} - \bar{y}_{0,C})$$

- The first term is the difference in means over time for the treated group.
  - This would be a good estimator of the policy effect only if no external factors changed across the two time periods.
- The second term is the difference in means over time for the control group.
  - Subtracting off this term hopefully controls for any changes in external factors that are common to both the treated and control groups, which will be the case when we have random assignment.

In this case, the DiD estimator can be interpreted as the average treatment effect.

Parallel trend assumption

- The standard two-group, two period difference-in-differences setup relies on the **assumption of parallel trends.**
- **Parallel trends assumes that the outcome y, in control and treatment groups, would have the same trend in the absence of the intervention.**
  - Prior to the intervention, y should move in the same direction for both groups.
- The standard DiD estimator measures the difference in estimated trends between the two groups.

Adding an additional control group

- If the parallel trends assumption is violated, we cannot be sure that the DiD estimator is identifying the effects of the policy or simply some other unaccounted factor causing different trends between these groups.
    - We can add flexibility by adding an additional control group.

Adding an additional control group

Example: The effects of expanding health care for low income families in a particular state.

- Let L denote low-income families (eligible for the policy) and M be middle-income families (not eligible).
- Let B denote states that implemented the policy and A be states that did not implement the policy.
- The policy is implemented in period 1 , but no policy exists in period 0.

The additional control group (income level) allows for more flexibility if we assume that any difference in trends in health outcomes between low and middle income families is similar across states.

Adding an additional control group

$$y = \beta_0 + \beta_1 dL + \beta_2 dB + \beta_3 dL * dB + \delta_0 d1 + \delta_1 d1 * dL + \delta_2 d1 * dB + \delta_3 d1 * dL * dB + u$$

$$\hat{\delta}_3 = \left[(\bar{y}_{1,L,B} - \bar{y}_{0,L,B}) - (\bar{y}_{1,M,B} - \bar{y}_{0,M,B})\right] - \left[(\bar{y}_{1,L,A} - \bar{y}_{0,L,A}) - (\bar{y}_{1,M,A} - \bar{y}_{0,M,A})\right]$$

$$\hat{\delta}_3 = \hat{\delta}_{DD,B} - \hat{\delta}_{DD,A} = \hat{\delta}_{DDD}$$

The **difference-in-difference-in-differences** estimator has two components:

- a DD estimator looking only at states that implemented the policy.
- a DD estimator looking only at states that did not implement the policy.

- If health trends between the L and M groups do not differ in non-implementation states, then the second component vanishes and we are back to the standard DiD setup.

- However, we include this second term to account for possibly different trends in the L and M groups that are common across both states A and B.